The Pennsylvania State University

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# PROGRESSION OF DESIGNER BEHAVIOR WHEN EXPLORING DIGITAL BUILDING DESIGN SPACES

A Dissertation in

Architectural Engineering

by

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# ABSTRACT

Design space exploration (DSE) strategies are increasingly used in architectural and engineering practice to generate and identify improved solutions. However, DSE often demands complex processes that require disciplinary knowledge and a firm grasp of exploration tools. While parametric platforms and optimization algorithms can enable a designer to rapidly construct and evaluate numerous design options in response to multi-disciplinary criteria, these tools may be less useful if not properly leveraged. Specifically, design students, who are developing their disciplinary knowledge, may not yet have the skills to thoroughly model and explore a design space. Alternatively, pre-built parametric models can provide performance feedback and allow for design exploration without extensive knowledge of the design tool. Such digital environments are useful for beginning designers to illustrate design relationships and to foster multi-objective thinking. Yet, these tools may not enable full design autonomy as is required in building design practice. Understanding how students and practitioners approach multi-objective design tasks using unrestricted DSE techniques can inform characteristics of their optimization strategies and reveal unexpected outcomes of working with design tools that provide performance feedback.

In response, I investigate the design space exploration behaviors of building designers at different educational stages, reporting on aspects of their design efficacy, multi-disciplinary thinking, and optimization techniques. Through a series of design studies, this body of work contributes to design process research and optimization education by examining how designers with different levels of experience seek improved design solutions in exploration tools. The first study examined how pre-design students performed in a parametric environment and how they prioritized different building design criteria. The second study asked mixed teams of architecture and engineering students to engage in a collaborative, parametric design task and investigated their efficacy and exploration when working in a parametric tool. While the first two studies focus on exploration in a pre-built parametric model, studies 3 and 4 expand the design space to prompt participants to develop their own parametric models and perform optimization strategies. Study 3 uses design sessions from graduate student participants to develop a code to describe and categorize optimization behaviors and study 4 expands on the work to include practitioners and compare their behaviors based on cognitive loads.

Across these studies, multiple streams of data were gathered and evaluated using varying research methods. Surveys and interviews were used to collect information about designers' self-perception, priorities, and design thinking, while the digital tools recorded the designers' performance, behavior, and eye movements. These datasets were analyzed and interpreted using different methods of evaluation including the Consensual Assessment Technique for design efficacy, the Situated FBS Ontology to define phases of the design process, and the Index of Cognitive activity to measure cognitive effort. While students were able to readily explore pre-built design spaces to develop solutions, they followed more rote patterns when developing a parametric model for design optimization compared to practitioners. Although parametric models can support rapid design exploration, optimization tools prompted more diversity of design processes and cognitive efforts for practitioners compared to students. These results challenge some established understandings of cognitive load, but also illustrate how experts will perform tasks with greater sophistication beyond basic step-by-step procedures. I conclude by relating the outcomes from the presented research to levels of designers' development and propose opportunities to use DSE tools in education strategies that can reinforce students' investigative design processes.

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# Chapter 1

# Introduction

As cities expand, infrastructure ages, and climate changes, the concerns of our built environment grow more complex. Our world requires architecture that accounts for environmental impacts, material resourcefulness, and energy efficiency while also addressing cultural, social, and programmatic needs. In response, building designers are tasked with developing high performing, cross-disciplinary design solutions. To do so, architects and engineers often integrate iterative computational tools into their design process to aid in the development and examination of multi-objective designs [1], [2]. One approach that enables designers to quickly probe design options is the process of design space exploration (DSE). DSE can refer to a systematic analysis of desirable design solutions in a space of tentative design points [3]. However, DSE can also more broadly refer to “the activity of exploring design alternatives prior to implementation” as described by Kang et al. [4]. Digital DSE tools, such as parametric models and optimization algorithms, can provide visual and performance feedback while enabling a designer to rapidly consider a range of design options with objective performance feedback. Figure 1-1 illustrates designers exploring a surface in a model space with editable variables and a plot comparing feedback of the model’s performance objectives.

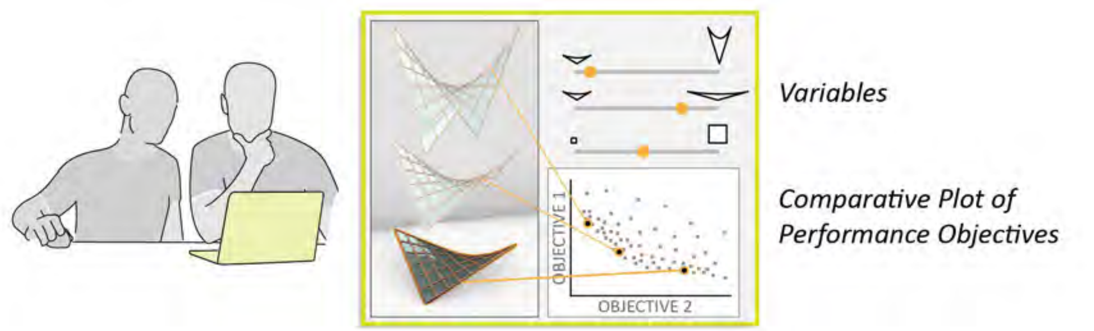


Figure **1-1**. An example of a parametric model with a model space, three variables, and a comparative plot of objective feedback.

DSE tools are used by both architects and engineers to achieve multi-objective goals [2], [5] and have prompted academics to investigate the broader application of DSE in parametric and optimization design processes. Previous research has considered decision-making procedures in parametric tools [6]–[9], the advantages of parametric design for technical performance [10]–[14], and the inclusion of parametric thinking in design education [15]–[17]. While research supports the incorporation of parametric strategies in building design for their exploration possibilities, parametric models alone do not provide design guidance. As an additional resource for developing and evaluating high performing buildings, some building design optimization tools can quickly generate many design options from a parametric model and highlight solutions that best align with quantitative goals provided by the designer. Research into building optimization processes has examined its algorithmic methods [18]–[22], considered potential benefits towards design performance [23]–[30] and investigated its applications in practice [31]–[33]. However, in considering optimization strategies, just because a designer knows *how* to use a tool, does not mean they know how to best *employ* a tool. To achieve the benefits of optimization techniques, designers must be prepared to incorporate performance feedback into their design decisions. For a student, who is learning how to use DSE tools while still developing their designerly skills, the benefits of design feedback may not be fully comprehended. When equipping designers to perform DSE strategies in practice, it is prudent to consider what preparations for multi-objective thinking are evident int their disciplinary instruction.

Computational tools have become integral in design education, but exploration strategies are not widely taught and may be difficult for students to apply. Additionally, learning how to use a digital tool can be more challenging than grasping the intended design lessons. Theories in mental workload associate learning with increased cognitive effort [34] which can limit task performance. Due to their experience in a task, experts are expected to exhibit lower cognitive loads and follow more precise design procedures compared to novice designers [35]. Optimization models produce new information about a design with each iteration and new projects may present novel design challenges. If designers with less DSE experience are still developing skill sets within a tool, their efficacy in decision-making may be restricted. Nevertheless, researchers and educators support that teaching optimization methods and incorporating more multi-objective thinking is necessary in leading design students into the future of professional practice [31], [36]. Teaching DSE tools alone may not be enough to ensure improved design performance, though. Understanding how designers with different levels of experience behave when exploring design spaces may better inform how to sculpt their education and identify opportunities to improve cognitive efficacy in DSE tool.

## 1.1 Thesis Scope

In response, this body of work examines the evolution of building designers' behavior and performance when exploring a parametric space for improved design solutions and makes suggestions for design stakeholders. Figure 1-2 provides the titles and order of the four studies included in this dissertation.

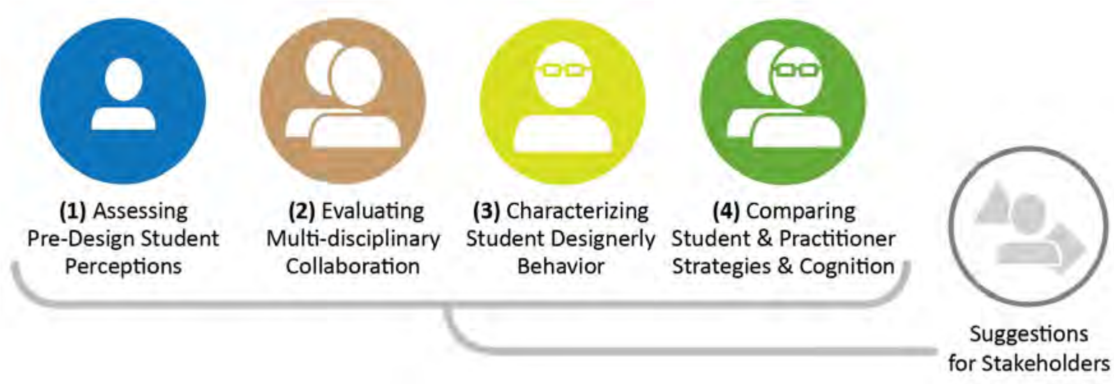


Figure **1-2**. Outline graphic summarizing the body of the dissertation.

The first study presented considers the proficiency and perceptions of pre-design students, prior to beginning their education as architects or engineers, when exploring a parametric model. The results of the study suggest that while pre-design students can navigate towards better performing designs in a parametric tool, they may struggle to address multi-disciplinary design concerns. The second study presents the efficacy and exploration techniques of mixed-discipline student design teams when collaborating in a parametric tool. It concludes that since expected performance differences based on team composition did not occur with the introduction of a parametric environment, tools that provide geometric and numeric design performance feedback may positively influence design process outcomes regardless of team disciplinary composition.

To better describe designer and DSE tool interaction, the third study reports the behaviors of graduate student designers when developing and evaluating a parametric model using optimization techniques. A code was developed to recognize optimization design actions and themes in the participants' optimization design strategies were determined. While some student participants integrated optimization feedback into their designs, not all achieved full or even partial integration, indicating a variety of approaches to optimization for students who are still learning how to best apply the tool. Broadening the research to encompass design behavior beyond theoretical application from student experience, the fourth study includes design session data from practitioners who have implemented building optimization techniques when developing built projects. Using various streams of mental workload metrics from established eye-tracking techniques, the paper from the fourth study compares the design strategies and cognitive efforts of the students to practitioners to deepen our understanding of design process across levels of experience in optimization tools. Aspects of the practitioners' mental workload aligned with established knowledge in design expertise, like having lower cognitive load, but they also exhibited a wider range of strategies and cognitive responses compared to students, confounding which techniques may lead to better informed building design decisions. Although tools that provide rapid performance feedback can support effective design space exploration, they may also introduce unexpected cognitive burdens when interpreting information about a design.

In the conclusion of this dissertation, I draw on contributions from these studies, paired with existing research and experience, to make suggestions for design stakeholders in academia and tool development. It is intended to encourage education of DSE techniques and resolve some of the challenges in using DSE tools for developing designers.

**References**

[1] A. Stals, S. Jancart, and C. Elsen, "Parametric modeling tools in small architectural offices: Towards an adapted design process model," *Des Stud*, vol. 72, p. 100978, Jan. 2021, doi: 10.1016/j.destud.2020.100978.

[2] T. Wortmann and B. Tunçer, "Differentiating parametric design: Digital workflows in contemporary architecture and construction," *Des Stud*, vol. 52, pp. 173–197, Sep. 2017, doi: 10.1016/j.destud.2017.05.004.

[3] J. M. P. Cardoso, J. G. F. Coutinho, and P. C. Diniz, "Additional topics," in *Embedded Computing for High Performance*, Elsevier, 2017, pp. 255–280. doi: 10.1016/B978-0-12-804189-5.00008-9.

[4] E. Kang, E. Jackson, and W. Schulte, "An approach for effective design space exploration," in *Foundations of Computer Software. Modeling, Development, and Verification of Adaptive Systems*. Monterey Workshop 2010., R. Calinescu and E. Jackson, Eds., Berlin: Springer, 2011, pp. 33–54. doi: 10.1007/978-3-642-21292-5_3.

[5] N. Gu, R. Yu, and P. A. Behbahani, "Parametric design: Theoretical development and algorithmic foundation for design generation in architecture," in *Handbook of the Mathematics of the Arts and Sciences*, Cham: Springer International Publishing, 2021, pp. 1361–1383. doi: 10.1007/978-3-319-57072-3_8.

[6] R. Yu, J. Gero, and N. Gu, "Architects' cognitive behaviour in parametric design," *Int J Arch Comp*, vol. 13, no. 1, pp. 83–101, Mar. 2015, doi: 10.1260/1478-0771.13.1.83.

[7] R. Oxman, "Thinking difference: Theories and models of parametric design thinking," *Des Stud*, vol. 52, pp. 4–39, Sep. 2017, doi: 10.1016/j.destud.2017.06.001.

[8] R. Yu, N. Gu, and M. Ostwald, "Comparing designers' problem-solving behavior in a parametric design environment and a geometric modeling environment," *Buildings*, vol. 3, no. 3, pp. 621–638, Sep. 2013, doi: 10.3390/buildings3030621.

[9] J. Lee, N. Gu, and A. P. Williams, "Parametric design strategies for the generation of creative designs," *Int J Arch Comp,* vol. 12, no. 3, pp. 263–282, Sep. 2014, doi: 10.1260/1478-0771.12.3.263.

[10] T. Wortmann and G. Nannicini, "Introduction to architectural design optimization," in *City Networks*, A. Karakitsiou, A. Migdalas, S. Rassia, and P. Pardalos, Eds., Springer, 2017, pp. 259–278.

[11] I. Anton and D. Tanase, "Informed Geometries. Parametric modelling and energy analysis in early stages of design," in *Energy Procedia*, Bucharest, Nov. 2016, pp. 9–16. doi: 10.1016/j.egypro.2015.12.269.

[12] D. Holzer, R. Hough, and M. Burry, "Parametric design and structural optimisation for early design exploration," *Int J Arch Comp*, vol. 5, no. 4, pp. 625–643, Dec. 2007, doi: 10.1260/147807707783600780.

[13] E. Touloupaki and T. Theodosiou, "Optimization of building form to minimize energy consumption through parametric modelling," *Procedia Environ Sci*, vol. 38, pp. 509–514, 2017, doi: 10.1016/j.proenv.2017.03.114.

[14] Q. Liu, X. Han, Y. Yan, and J. Ren, "A parametric design method for the lighting environment of a library building based on building performance evaluation," *Energies (Basel)*, vol. 16, no. 2, p. 832, Jan. 2023, doi: 10.3390/en16020832.

[15] M. A. Schnabel, "Learning parametric designing," in *Industrial Engineering*, IGI Global, 2013, pp. 197–210. doi: 10.4018/978-1-4666-1945-6.ch013.

[16] K. Romaniak and S. Filipowski, "Parametric design in the education of architecture students," *World Transaction on Engineering and Technology Education*, vol. 16, no. 4, pp. 386–391, 2018.

[17] A. P. Ponzio, M. G. Gonzaga, M. P. de Castro, A. Vale, U. M. Bruscato, and W. Mog, "Parametric design learning strategies in the context of architectural design remote teaching," in *SIGRADI 2021 Designing Possibilities Ubiquitous Conference*, 2021, pp. 1077–1088.

[18] J. Felkner, E. Chatzi, and T. Kotnik, "Interactive particle swarm optimization for the architectural design of truss structures," in *2013 IEEE Symposium on Computational Intelligence for Engineering Solutions (CIES)*, J. Felkner, E. Chatzi, and T. Kotnick, Eds., Singapore: IEEE, Apr. 2013, pp. 15–22. doi: 10.1109/CIES.2013.6611723.

[19] R. T. Marler and J. S. Arora, “Survey of multi-objective optimization methods for engineering,” *Structural and Multidisciplinary Optimization*, vol. 26, no. 6, pp. 369–395, Apr. 2004, doi: 10.1007/s00158-003-0368-6.

[20] V. Machairas, A. Tsangrassoulis, and K. Axarli, “Algorithms for optimization of building design: A review,” *Renewable and Sustainable Energy Reviews*, vol. 31, pp. 101–112, Mar. 2014, doi: 10.1016/j.rser.2013.11.036.

[21] K. Nielson and M. Khademi, “CoOptimise: Exploring human and machine cooperation in optimization and design,” In *eCAADe 25: Shock! Sharing of Computable Knowledge*. Sep. 2017.

[22] A.-T. Nguyen, S. Reiter, and P. Rigo, “A review on simulation-based optimization methods applied to building performance analysis,” *Appl Energy*, vol. 113, pp. 1043–1058, Jan. 2014, doi: 10.1016/j.apenergy.2013.08.061.

[23] N. C. Brown and C. T. Mueller, “The effect of performance feedback and optimization on the conceptual design process,” in *International Association of Spatial Structures Annual Symposium*, Tokyo, Sep. 2016. [Online]. Available: https://www.researchgate.net/publication/316107726

[24] L. Wang, H. Wong Nyuk, and S. Li, “Facade design optimization for naturally ventilated residential buildings in Singapore,” *Energy Build*, vol. 39, no. 8, pp. 954–961, Aug. 2007, doi: 10.1016/j.enbuild.2006.10.011.

[25] T. Wortmann, “Model-based optimization for architectural design: optimizing daylight and glare in grasshopper,” *Technology Architecture Design*, vol. 1, no. 2, pp. 176–185, Nov. 2017, doi: 10.1080/24751448.2017.1354615.

[26] R. A. Danhaive and C. T. Mueller, “Combining parametric modeling and interactive optimization for high-performance and creative structural design.,” in *Proc., IASS Annual Symp*, Madrid, Spain: International Association for Shell and Spatial Structures, 2015.

[27] X. Liu, L. Wang, and G. Ji, “Optimization-Based Design Exploration of the Mutual Influence Between Building Massing and Façade Design,” in *2022 Annual Modeling and Simulation*

*Conference (ANNSIM)*, IEEE, Jul. 2022, pp. 487–499. doi: 10.23919/ANNSIM55834.2022.9859405.

[28] L. E. Hinkle, J. Wang, and N. C. Brown, "Quantifying potential dynamic façade energy savings in early design using constrained optimization," *Build Environ*, vol. 221, p. 109265, Aug. 2022, doi: 10.1016/j.buildenv.2022.109265.

[29] J. M. Broyles, M. R. Shepherd, and N. C. Brown, "Design optimization of structural–acoustic spanning concrete elements in buildings," *J Arch Eng*, vol. 28, no. 1, Mar. 2022, doi: 10.1061/(ASCE)AE.1943-5568.0000520.

[30] X. Shi and W. Yang, "Performance-driven architectural design and optimization technique from a perspective of architects," *Autom Constr*, vol. 32, pp. 125–135, Jul. 2013, doi: 10.1016/j.autcon.2013.01.015.

[31] J. M. Cichocka, W. N. Browne, and E. Rodriguez, "Optimization in the architectural practice," in *22nd International Conference of the Association for Computer-Aided Architectural Design Research in Asia (CAADRIA)*, P. Janssen, P. Loh, A. Raonic, and M. A. Schnabel, Eds., Hong Kong: The Association for Computer-Aided Architectural Design Research in Asia, 2017, pp. 387–397.

[32] D. Yang, L. Wang, and G. Ji, "Optimization-assisted building design - cases study of design optimization based on real-world projects," in *the 40th Conference on Education and Research in Computer Aided Architectural Design in Europe (eCAADe 2022)*, B. Pak, G. Wurzer, and R. Stouffs, Eds., Ghent, 2022, pp. 609–618.

[33] D. Yang, Y. Sun, M. Turrin, P. von Buelow, and J. Paul, "Multi-objective and multidisciplinary design optimization of a large sports building envelopes: a case study," in *International Association of Shell and Spatial Structures 2015 Amsterdam Symposium: Future Visions - Computational Design*, Amsterdam, 2015, pp. 1–14.

[34] J. Sweller, “Cognitive load during problem solving: Effects on learning,” *Cogn Sci*, vol. 12, no. 2, pp. 257–285, Jun. 1988, doi: 10.1016/0364-0213(88)90023-7.

[35] M. Kavakli and J. S. Gero, “Strategic knowledge differences between an expert and a novice designer,” in *Human Behavior in Design*, U. Lindemann, Ed., Berlin, Heidelberg: Springer Berlin Heidelberg, 2003, pp. 42–52. doi: 10.1007/978-3-662-07811-2.

[36] W. Peng, “Teaching reform and optimization design of architectural performance course,” *Int J Soc Sci Edu Res*, vol. 4, no. 9, pp. 48–52, 2021.

# Chapter 2

# Background

Improving the built environment for the benefit of our world requires effective design strategies and relies on formative design tools. How we prepare designers to respond to complex, multi-disciplinary design challenges in digital environments can impact their design processes and influence their design efforts. In evaluating behaviors of designers, from pre-design students to practitioners, when exploring building design spaces, the work presented in this dissertation contributes to the rich body of research that strives to capture the increasing complexity of design processes and supports opportunities for improvement in the pursuit of building design.

## 2.1 Design Space Explorations

In a broad sense, design space exploration (DSE) can be defined as searching a set of design options prior to implementation [1] but can also refer to seeking a solution that satisfies desirable objective goals from a set of tentative design points [2]. In architectural design, tentative design points can have associated qualities and quantities that represent the characteristics of a building. Figure 2-1 provides an example of a model with a design space and an objective space. In this example, the tower has four possible solutions defined by its two variables, height and width. In each solution, the height and width are different and are also inversely related. In the Design Space, the variables of each solution are plotted to illustrate their relationships. The model also has two objectives, structure and sunlight, which are plotted in the Objective Space with representative performance scores. Note that a performance score is not the same as the actual value of the objective. In this example sunlight and structure do not have the same units nor do they share a similar relationship within their dimensions. More daylight and less structure are generally considered advantageous to reduce artificial light and decrease construction costs. To better capture the complexity of these goals, objectives are often normalized so they can be compared without units and organized so that “0” is the goal of all objectives in an optimization algorithm. However, the objective goals of a design are frequently inversely related such that no perfect numeric solution exists. When this occurs, a designer may prioritize certain objectives, or they will rely on their own intuition and select a design based on criteria not captured in the objective space. Manually generating different model iterations with multiple design variables is a time intense process and exploring model performances individually also requires repetitive effort. Alternatively, digital tools, such as parametric models, readily enable a designer to produce design variations [3] and optimization tools can rapidly search for “better” performing design solutions, supporting more efficient design processes [4]–[6].

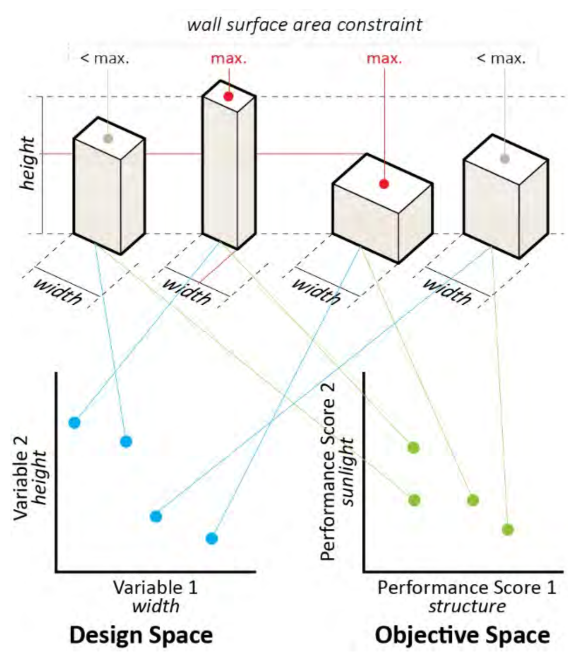


Figure **2-1.** Example tower model with a Design Space and an Objective space, illustrating the relationship between variables and objectives.

### 2.1.1 Parametric Tools

Parametric tools allow for DSE and are supported by previous research as a viable environment for design decision-making that build on established models of design process. There is much literature discussing theories of design process [7]–[10], with most models establishing a phase for problem definition, one for design development, and one of resolution analysis. Some researchers have also considered how a designer knows which phase to perform, such as Cross' *designerly ways of knowing* [11] which describes a designers' cognitive reflection on design actions. Distinguishing conscience decisions during the design phases is important when accounting for potential influences on design thinking. As digital tools become integral to design formulation, researchers have also considered how technology may impact the design process [12]–[14]. Literature shows that when a computer is used to support or make key decisions, there are different schemes to identify a designer's cognitive or computational decisions [15], [16]. However, other research differentiates that a parametric model cannot replace the ingenuity of a human designer [17]. In a general definition, Woodbury describes parametric design as an exploration of associated relationships of geometric concepts [18]. Oxman adds to this definition stating "the designer 'designs' the code of the parametric schema in order to design the design object" [19]. Although designing a parametric model may supersede designing the building as a cognitive effort, Oxman also acknowledges that parametric design is "a unique and distinctive model of creativity and innovation in parametric design thinking." [19]. Oxman's assessment re-affirms what earlier research into parametric design and cognition has established: parametric thinking is legitimate approach to exploring and solving complex design problems [20]–[23].

In addition to enabling viable design processes, incorporating parametric tools into parametric thinking can improve the performance of built designs [24], [25]. Parametric tools can readily provide technical performance feedback, which is beneficial for multi-disciplinary exploration [26], [27]. They have been useful for producing and evaluating building criteria such as architectural forms [28], structural design [29], building energy [30], daylight and glare [31], [32], and urban planning [28]. In application of built work, parametric tools are used by esteemed design firms, such as ARUP [33], Foster + Partners [34], NBBJ Architects [15], and UNStudio [15]. They are also used by research designers, such as the Block Group, who employed parametric strategies to explore forms with structural and material feedback to develop their innovative Beyond Bending pavilion at the 2016 Venice Biennale [35]. In all these examples, though, design teams are composed of either both architects and building engineers or designers with multi-disciplinary backgrounds to draw upon the expertise of both professions. DSE tools can support multi-objective problem solving and encourage collaborative efforts, but the users must also have a designerly sense of effective design decisions.

#### *2.1.1.1 Multi-Disciplinary Design*

Multi-disciplinary design relies on design tools that can produce various streams of feedback and requires that designers interpret the results. The existence of a design team with both architects and building engineers, however, does not guarantee effective collaboration. While diversity in design teams can lead to more creative solutions, this outcome is dependent on a shared understanding and conducive design environment [36]. Unfavorable to collaboration, many design tools inherently favor the aptitude of specific professions to allow for expertise of design, such as sketching and geometric modeling for architects and detailed analysis tools for engineers. However, the multi-objective feedback provided by parametric models, such as Grasshopper, may allow designers to approach the design environment with more shared influence and integrate feedback from the tools more readily. Previous research has shown that designers' cognitive effort towards design knowledge can change during parametric design, relying more on the tool's rule algorithms for design decisions as the designers progressed through the design session [20]. This is useful in considering design behavior in parametric tools and suggests how the tools could be leveraged for multi-disciplinary design. While a designer must know how to work in a parametric space, gaps in their disciplinary expertise may be supported by the tool's logic. In addition, parametric tools enable designers to generate numerous design options with multiple design criteria. This process results in a massive search space, though, and exploring each design individually for its objective performance is time intensive and requires automation [2]. Additional tools and techniques are required to further support effective DSE strategies with multi-objective considerations.

### 2.1.2 Optimization Tools

To help parse design solutions from a parametric space, designers use optimization algorithms to rapidly search the design space for solutions that meet their desired goals. This process supports designers in making more informed decisions [37]. However, objective spaces rarely contain one, "best" solution and a designer may iterate between their model and the optimization tool's feedback, honing in on a design solution that they desire [38]. Figure 2-2 illustrates the cyclical process between a designer and the tool as the designer refines and variables in the design space. While the optimization tool provides informed feedback with each iteration, selecting a final design will often depend on more than just quantitative goals, accounting for qualitative requirements, relying on the designer's intuition, and, perhaps, responding to a client's preference.

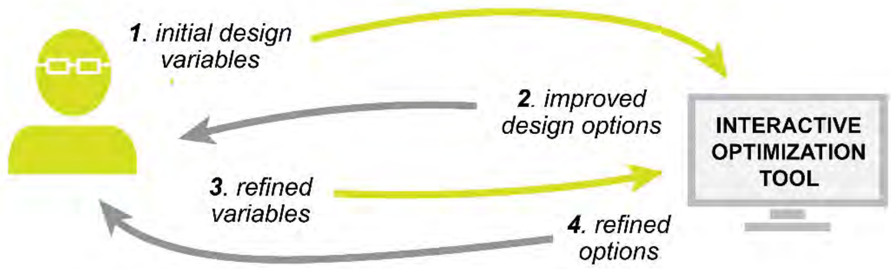


Figure **2-2.** The iterative design process between a designer and an optimization tool as the designer refines the design space to a solution that they find desirable.

Optimization tools can thus help designers make informed decisions while still allowing for design freedom. Nielson reports optimization as an opportunity for human and machine cooperation [39] and Liu et al. describes optimization-based design exploration as a mutual influence between building massing and façade design [40]. Additional research reports the benefits of optimization on design performance such as for building simulations [41], [42], structural performance [43]–[45], and enclosure design [46]–[48]. While optimization techniques allow for rapid exploration and quick performance feedback, some designers criticized digital design space exploration for its limitation in design thinking and potential design fixation compared to traditional sketching processes [49]. Nevertheless, optimization strategies have been used in a variety of practices [37], [50] and help designers find improved design solutions to complex design problems [51]–[53]. For optimization tools to be useful, though, a designer must know how to effectively incorporate optimization strategies into their design processes and their design education may equip them to use complex DSE tools.

## 2.2 Designer Education

With the broadening application of DSE strategies in practice, preparing students to join design professions may require their education to incorporate more DSE techniques and reinforce multi-objective thinking. However, research in design identity suggests that students may not be prepared to respond to cross-disciplinary design tasks as they can behave in a way they find emblematic to their identified profession [54], [55]. While architecture students are strong at creative thinking, they may shy away from rigorous quantitative analysis [56] and engineering students can sometimes struggle to solve open ended problems [57]. These limitations may curb their efficacy as designers when responding to multi-disciplinary design tasks and influence their collaborative decision-making in mixed design teams. As a potential solution, parametric tools with design performance feedback can bridge gaps in disciplinary understanding.

### 2.2.1 Disciplinary Distinctions

Architects and engineers are trained to address different design concerns which allows for expertise to support better performing buildings, however, their scopes are rarely exclusive. Although building engineers generally have technical specialties, such as in structural or mechanical systems, they still work with an architect to achieve a wholistic vision. And while architects may be responsible for addressing programmatic needs, visual appearance, and project cohesion, they are also concerned with performative characteristics, such as enclosure systems, and construction management, such as cost and timeline. Despite their overlaps in design considerations, the professions' training distinguishes them by providing engineers with a strong math- and science-based context for design while architects receive extensive practice in spatial design and idea expression. Moreover, in the United States, two different governing bodies oversee accreditation of architecture and engineering degree programs: the National Architectural Accrediting Board (NAAB) and the Accreditation Board for Engineering and Technology (ABET). These agencies require different criteria of a curriculum before approving an accredited degree. For example, it is expected that architecture students complete a series of design studios while engineers must understand calculus.

Architecture and engineering were not always independent professions, though. Prior to the industrial revolution, a "building master" was responsible for all design aspects of a building, but with advances in technology, materials, and construction techniques, expertise emerged. There was strategic value in distributing design responsibility, allowing for innovative approaches, and improving design performance. In addition, around the turn of the 20th century, specificity in building design was further delineated with the growth of institutional education. A person intrigued by engineering or architecture could pursue a degree that aligned with their topical interests and cognitive strengths. While disciplinary distinctions have led building designers to achieve monumental feats in building construction, they have also led to assumed contention. In his book titled "Architect and Engineer: A Study in Sibling Rivalry," Andrew Saint explains how architects and engineers have too neatly compartmentalized their own histories and capabilities, driving them apart and limiting what they can collectively achieve [58]. He adds that the professions are more connected than many people tend to believe, and the disciplines cannot work separate from each other. Building educators have called for improved understanding between the professions [59], with books discussing the overlaps in their disciplinary interests [60-62]. Nevertheless, recent research acknowledges that the professions have different preferences for tools, like building performance simulations [63].

With advances in multi-disciplinary technology, such as collaborative design tools and parametric environments, there is an opportunity to reassimilate responsibilities and design processes of architects and engineers. Although paradigm shifts are not exclusive to academic venues, disciplinary education may support more multi-objective thinking with introductions to parametric techniques and optimization thinking.

### 2.2.2 Design Education in Optimization

Although parametric strategies have been incorporated in student education [64]–[66], concepts of optimization are not prevalently included in traditional architectural or engineering education. While some educators lead courses that directly teach optimization strategies [67]–[69], there are not established approaches for instruction of systematic improved design performance in these domains, which has been criticized as a limitation to the tools' application [70]. In addition, there is support from educators that teaching optimization methods in architecture is important in leading architecture students into the future of building design [71] and that there is a need for more multi-objective thinking in design fields [50]. However, the advantages of optimization techniques may not be immediately evident to students without understanding the challenges faced by practitioners when navigating complex design objectives. Constructing a parametric model and using optimization tools effectively requires skills in the design environment and practice in addressing multiple design goals. Regardless of experience, though, projects can vary by their requirements and contexts which may prompt practitioners to re-learn about their design approaches. To better educate student designers about advantageous optimization strategies, it is useful to differentiate novice and expert levels of understanding in DSE tools.

### 2.2.3 Expertise in Design

There is much consideration given design expertise, with researchers reporting differences of novice and expert design approaches in terms of idea formulation [72], the kinds of knowledge they use [73], and patterns in their cognitive effort [74]. In general, experts are expected to use more precise strategies and exert less cognitive effort compared to novices [72]–

[75]. Increased cognitive load is associated with the retention of new information [76] which requires working memory to process new data into long-term, permanent knowledge [77], [78]. As a result, expertise often aligns with less cognitive load since experts are not interpreting new data. However, building design frequently evokes novel solutions with each new project, prompting the generation of new information that may challenge an expert's mental effort [79]. In addition, task complexity can demand more working memory [80], which can impact a designer's performance [81]. Building design exploration requires the consideration of many criteria that often have complicated relationships. As a result, navigating optimization design tasks may impact design cognition in unexpected ways.

Understanding how cognition, task complexity, and design expertise unintentionally influence DSE strategies can reveal which design approaches lead to more effectual design outcomes. They may also suggest opportunities to improve DSE education. From studying the relationship between cognition and new information, researchers have been able to influence instruction tactics for more effectual learning. Kirschner states "…limitations of working memory can be circumvented by coding multiple elements of information as one element in cognitive schemata, by automating rules, and by using more than one presentation modality" [82]. In short, learners are more likely to retain information when it is presented in several forms and delivered with consistency. This pedagogical advice is best applied during DSE education, as opposed to in practice, since exploration and optimization is a complex task [2] and may be difficult to refine later in career development. In addition, architectural proficiency in rapidly evolving computational tools can be transient [79], which challenges what may qualify as "expertise" in building design. For many research studies that compare designers' level of knowledge, an "expert" is measured by years of experience in a field. However, a recent paper by Tan [83] suggests that traditional understandings of expertise may not fully capture a designer's understanding of a topic. As an alternative, Tan describes expertise as an extension of experience, adaptability, perceptiveness, and motivation. When responding to complex design problems in evolving DSE environments, a designer's ability to synthesize, reflect, and adapt is more telling than the number of years a designer has worked in their field. Moreover, design capability and evidence of disciplinary knowledge may change depending on the tools being used and the complexity of the design task.

In considering the evolution of designer competence and behavior in DSE environments, this dissertation relies on research in parametric design, multi-disciplinary education, and design process cognition to present four new studies that contribute to design understanding. It also makes suggestions for DSE stakeholders, such as instructors in academia and tool developers, to better connect research findings to practice. Below, I briefly introduce each study and outline the research gap it addresses, methods used, and conclusions taken from the results. In the concluding remarks of this dissertation, I discuss opportunities to apply the information collected from the studies to design education.

## 2.3 Research Methods

A series of studies were conducted which considered the perceptions, efficacy, and behaviors of designers when working in DSE tools, summarized in Fig. 2-3. The studies focused on stages of designer development from before beginning their professional education, to solving multi-disciplinary problems as students, and to completing complex design challenges in practice. The studies' design tasks and environments prompted greater exploration as the designers' level of experience increased. Pre-built parametric models were used in the first two studies with an unconstrained design space used in studies three and four. I provide an overview of each studies' research goals, the methods used, and a summary of the results which provide insight into designerly behavior in DSE activities. The studies reveal opportunities to enhance designer education in multi-objective thinking and design exploration.

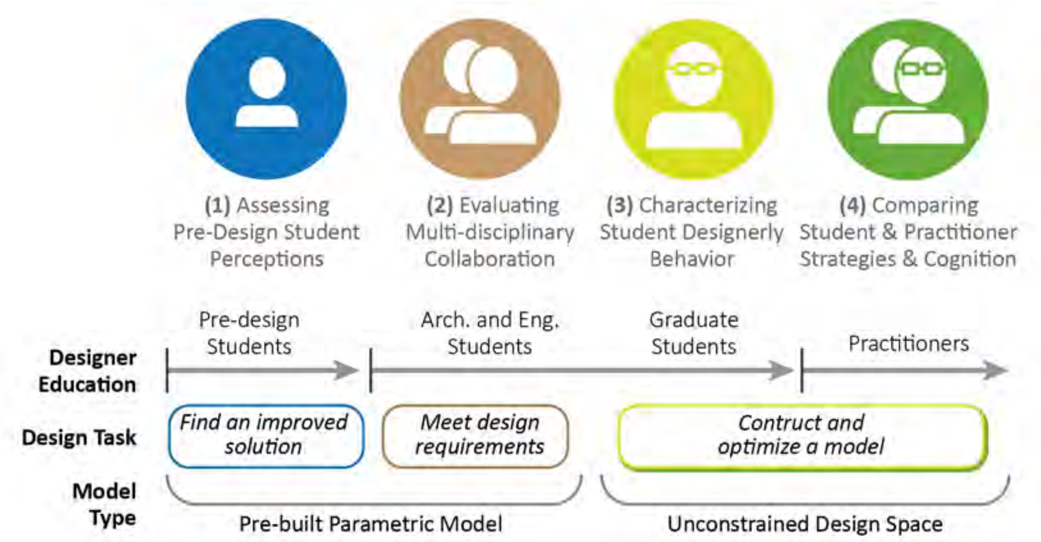


Figure **2-3.** Outline of the four studies with the participants' level of education, a summary of the design task goal, and the type of model space used.

### 2.3.1 Assessing Pre-Design Student Perception

Before evaluating design behavior in complex design tools, the performance of potential designers in an approachable design space was considered. A design study, conducted in a parametric modeling tool with visual objective feedback, captured pre-design students' perceptions of self-competency in engineering related subjects and compared their performance behaviors in the tool to the design criteria that they valued. The study asked, how do pre-design students' self-competency in STEM relate to their design exploration, performance, and perception of goals when working a parametric space. From this study, the more exclusive self-competency a student felt in STEM subjects, the more they iterated in the tool and the better their final designs performed. However, the STEM self-competent students also ranked appearance lower than the quantitative criteria. While it was expected that STEM self-competent students would create improved design solutions and it is advantageous for them to iterate more in the parametric design space, it may be that engineering oriented students are inclined to not consider criteria that are not included in their subject of interest. This may limit their efficacy when responding to multidisciplinary design tasks in their career and influence their efficacy in diverse design teams. Also, 83% of all students submitted solutions that performed better than the starting design, suggesting that they were able to effectively respond in the parametric design tool despite having never used it before. It may be that parametric exploration can enable performative design decisions without extensive design experience.

*This work is published in:*

Bunt, S., Hinkle, L., Walton, A. & Brown, N. (2023). Relationship between high school STEM Self-competency and behavior in a parametric building design activity. In 2023 ASEE Annual Conference & Exposition Proceedings.

### 2.3.2 Evaluating Student Team Multi-Disciplinary Collaboration

Design teams are often comprised of diverse members to address multi-disciplinary considerations, which can lead to more creative solutions, but this outcome is dependent on a shared understanding between teammates and a conducive environment [84]. The behavior of diverse building designers when given multi-objective tasks may not yield the predicted results of increased creativity and design efficacy as they have their own criteria and tools for achieving their disciplinary goals. To better understand this division of effort, a design study was conducted which asked pairs of Architect+Architect, Engineer+Engineer, and Architect+Engineer to respond to a design task with both architecture and engineering focused criteria in an equally approachable parametric model. The research asked, how does team composition relate to design efficacy and exploration in a shared, live parametric design environment? While it was expected that the teams of mixed designers would develop more effective solutions, as evaluated by 4 design experts, no team type developed better performing designs with statistical significance. No team type displayed differentiating exploration strategies either. It may be that student designers are not yet distinguishable enough in their discipline to display differences in design strategies or that a parametric modeling tool with both qualitative and quantitative feedback can benefit the efforts of a design team in absence of the design member counterpart. More detailed research was needed focusing on the design behavior of designers when developing and exploring a design space.

*This work is primarily published in:*

Bunt, S. & Brown, N. (2023). Design efficacy and exploration behavior of student architect-engineer design teams in shared parametric environments. Buildings 13(5), 1296. *https://doi.org/10.3390/buildings13051296*

### 2.3.3 Characterizing Student Designerly Behavior

While optimization techniques have increasingly been used in design fields, the exact behaviors of designers when developing a model for optimization is less clear. In response, a third design study asked: what behaviors do student designers, trained in optimization techniques, exhibit when designing in a parametric space with optimization goals? The study documented and coded the behaviors of student designers when creating a design in a parametric space with multi-disciplinary design goals and optimization strategies. Gero and Kannengiesser's Situated FBS Ontology [85] was used to identify event shifts in the optimization design process, isolating design techniques in the designers' decision-making, and allowing the strategies of design optimization students to be compared. This work reported iterative loops in optimizations strategies including complete cycles in which the designer integrated feedback from the optimization tool into their design and course cycles in which the designer did not review the performance feedback from the tool at all. This work, qualitative in nature, provides a language by which to further describe design behavior in optimization and allows for more specific, quantitative analysis in future research questions. In particular, understanding how the design behaviors of students compare to that of practitioners is important in making suggestions for the academic development of building designers.

*This work is published in:*

Bunt, S., Berdanier, C. G. P., & Brown, N. C. (2023b). Observing Architectural Engineering Graduate Students' Design Optimization Behaviors Using Eye-Tracking Methods. *Journal of Civil Engineering Education*, 149(4). *https://doi.org/10.1061/JCEECD.EIENG-1889*

### 2.3.4 Comparing Student and Practitioner Strategies and Cognition

A fourth study asked: how do student and practitioner behaviors and cognitive loads compare when designing in a parametric space with optimization goals? To address this question, the study from part three was expanded to include design sessions from building design practitioners. Their design behaviors were reported by session events and organized into optimization cycles. To discuss differences in in their design thinking, the cognitive responses of students and practitioners were compared using three eye-tracking metrics: scaled Index of Cognitive Activity [86], fixation count, and fixation durations. Although research suggests that eye behavior can indicate changes in mental effort when interpreting new information, it is possible that design optimization tasks elicit unexpected cognitive responses. In general, it is expected that experts express lower cognition loads compared to novices because they are less likely to be learning while performing a design task. While the practitioners in this study demonstrated lower overall cognitive loads compared to the students, they also had a wider spread of cognitive responses in the three metrics and used a greater variety of design strategies. The practitioners more consistently incorporated design feedback from the optimization tools, but also opted for more design autonomy in two of the sessions. Meanwhile, differences in student techniques and cognitive efforts were less diverse. This work supports presumptions of decreased cognitive effort for practitioners, but also confounds expectations of individual design behavior in optimization strategies. It may be that optimization tasks elicit distinct design processes when navigating design knowledge with parametric modeling and layering algorithmic performance feedback. Future work will organize the sessions by optimization cycles, rather than design experience, to examine cognition in complete design events and identify optimization procedures that may lead to lower cognitive effort.

*This work will be submitted to a future journal.*

### 2.3.5 Concluding Remarks

In the conclusion of my dissertation, I make suggestions for design stakeholders to better connect the research to opportunities for application. I make recommendations to educators for how to use DSE environments as instructional tools depending on the experience of their students and their teaching goals. For optimization tool developers, I illustrate different ways to provide performance feedback and reduce erroneous streams of information. In acknowledging a gap between existing DSE tools and instruction of complete optimization strategies, I propose an optimization teaching tool that guides learners through the steps of incorporating design feedback into their decisions. Through a series of instructional phases, it allows for increased design freedom while prompting optimization behavior. The tool would be a pre-built model in an approachable design environment but could provide numerous examples and illustrate multi-disciplinary design thinking through different building typologies. These suggestions are guided by the results of the four presented studies which are outlined in Table 2-1. The table states gaps in existing research, highlights the studies' research questions, describes the methods used, and summarizes the outcomes.

Table **2-1**. Contribution stating the gap in research, research questions, methods used to address the question, and the outcomes from the research.

| GAP | RESEARCH QUESTION | METHODS | OUTCOME |
|---|---|---|---|
| (1) Assessing Pre-Design Student Perceptions | | | |
| Pre-design students may be influenced to perform in a way emblematic to an architect or engineer prior to their professional training, impacting their cross-disciplinary design thinking. | How do **pre-design students'** self-competency in STEM relate to their design exploration, performance, and perception of goals when working in a parametric design space? | Using a design study with 107 pre-design students, compare their exclusive STEM Self-competency to design exploration, performance, and criteria priorities. | -- Greater STEM SC correlated with more exploration and better design performance<br>-- More exclusive STEM SC may lead to more discipline narrow design considerations when working in a parametric design space.<br>-- Students were able to effectively explore the design space. |
| (2) Evaluating Multi-disciplinary Collaboration | | | |
| Student archs. and engs. may create better performing design solutions when working in mixed teams, as opposed to teams of their own profession, but only if the environment is conducive to their design collaboration. | How does team composition relate to **design efficacy and exploration** in a shared, live parametric design environment? | Compare efficacy and exploration of A+A, E+E, and A+E designers when responding to a task with both architectural and engineering goals in an equally accessible parametric tool. | -- Diverse design teams did not develop more effective solutions in the shared design space.<br>-- Parametric tools with multi-disciplinary feedback may benefit multi-disciplinary thinking across both disciplines. |
| (3) Characterizing Designerly Behavior | | | |
| Optimization tools provide iterative design analysis. When constructing and exploring a design space for optimization, students may use different techniques to incorporate feedback when addressing complex problems. The variety of these strategies is unclear. | What **behaviors do student designers,** trained in optimization techniques, exhibit when designing in a parametric space with optimization goals? | Provide student designers with an optimization design task and document their processes using eye-tracking, screen recordings, and follow-up interviews. Apply established protocol analysis methods, such as FBS situated ontology, to characterize their behavior. | -- Three levels of optimization integration were identified, indicating that graduate students, who are still learning, may not fully include optimization feedback in their design decisions.<br>-- Timing of optimization design events may differ by discipline, but observed strategies are not unique to one type of designer. |
| (4) Comparing Student and Professional Strategies | | | |
| Optimization techniques may be used differently in practice than in school. It is unclear what behaviors practitioners, who have more professional experience applying optimization, may exhibit compared to student designers. | How do **student and practitioner behaviors and cognitive loads** compare when designing in a parametric space with optimization goals? | Include design sessions of practitioners with students to compare the similarities and differences of their designerly behaviors and cognitive loads. | -- Practitioners showed lower overall cognitive loads compared to students, but also exhibited a wider spread of design strategies. While practitioners opted for more design autonomy, the students followed more similar proceedures with varying levels of feedback integration.<br>-- Cognitive behavior may be better understood by optimization cycles than design experience. |

**References**

[1] E. Kang, E. Jackson, and W. Schulte, “An approach for effective design space exploration,” in *Foundations of Computer Software. Modeling, Development, and Verification of Adaptive Systems. Monterey Workshop 2010.*, R. Calinescu and E. Jackson, Eds., Berlin: Springer, 2011, pp. 33–54. doi: 10.1007/978-3-642-21292-5_3.

[2] J. M. P. Cardoso, J. G. F. Coutinho, and P. C. Diniz, “Additional topics,” in *Embedded Computing for High Performance*, Elsevier, 2017, pp. 255–280. doi: 10.1016/B978-0-12-804189-5.00008-9.

[3] M. Turrin, P. von Buelow, and R. Stouffs, “Design explorations of performance driven geometry in architectural design using parametric modeling and genetic algorithms,” *Advanced Engineering Informatics*, vol. 25, no. 4, pp. 656–675, Oct. 2011, doi: 10.1016/j.aei.2011.07.009.

[4] C. T. Mueller and J. A. Ochsendorf, “Combining structural performance and designer preferences in evolutionary design space exploration,” *Autom Constr*, vol. 52, pp. 70–82, Apr. 2015, doi: 10.1016/j.autcon.2015.02.011.

[5] D. J. Gerber and S.-H. E. Lin, “Designing in complexity: Simulation, integration, and multidisciplinary design optimization for architecture,” *Simulation*, vol. 90, no. 8, pp. 936–959, Aug. 2014, doi: 10.1177/0037549713482027.

[6] N. C. Brown, V. Jusiega, and C. T. Mueller, “Implementing data-driven parametric building design with a flexible toolbox,” *Autom Constr*, vol. 118, p. 103252, Oct. 2020, doi: 10.1016/j.autcon.2020.103252.

[7] N. Cross and N. Roozenburg, “Modelling the design process in engineering and in architecture,” *Journal of Engineering Design*, vol. 3, no. 4, pp. 325–337, Jan. 1992, doi: 10.1080/09544829208914765.

[8] B. Lawson, *How Designers Think*, 4th edition. Norfolk, UK: Routledge, 2006. doi: 10.4324/9780080454979.

[9] N. Cross, *Design Thinking: Understanding how Designers Think and Work*. Oxford: Berg, 2011.

[10] P. Rowe, *Design Thinking*. Cambridge, MA: MIT Press, 1987.

[11] N. Cross, "Designerly ways of knowing," *Des Stud*, vol. 3, no. 4, pp. 221–227, Oct. 1982, doi: 10.1016/0142-694X(82)90040-0.

[12] M. McCullough, W. Mitchell, and P. Purcell, *The Electronic Design Studio: Architecture, Media and Knowledge in the Computer Era*. London, England: MIT Press, 1990.

[13] R. E. Oxman, "Precedents in design: a computational model for the organization of precedent knowledge," *Des Stud*, vol. 15, no. 2, pp. 141–157, Apr. 1994, doi: 10.1016/0142-694X(94)90021-3.

[14] M. Burry, *Scripting Culture: Architectural Design and Programming*. AD Primers, Wiley and Sons, 2011.

[15] I. Caetano, L. Santos, and A. Leitão, "Computational design in architecture: Defining parametric, generative, and algorithmic design," *Frontiers of Architectural Research*, vol. 9, no. 2, pp. 287–300, Jun. 2020, doi: 10.1016/j.foar.2019.12.008.

[16] R. Yu and J. Gero, "An empirical foundation for design patterns in parametric design," in *Association for Computer-Aided Architectural Design Research in Asia.*, Hong Kong, 2015, pp. 551–560.

[17] N. A. Megahed, "Digital realm: Parametric-enabled paradigm in architectural design process," *International Journal of Architecture, Engineering and Construction*, vol. 4, no. 3, pp. 174–183, Sep. 2015, doi: 10.7492/IJAEC.2015.018.

[18] R. Woodburry, *Elements of Parametric Design*. London: Routledge, 2010.

[19] R. Oxman, "Thinking difference: Theories and models of parametric design thinking," *Des Stud*, vol. 52, pp. 4–39, Sep. 2017, doi: 10.1016/j.destud.2017.06.001.

[20] R. Yu, J. Gero, and N. Gu, "Architects' cognitive behaviour in parametric design," *International Journal of Architectural Computing*, vol. 13, no. 1, pp. 83–101, Mar. 2015, doi: 10.1260/1478-0771.13.1.83.

[21] J. H. Lee, N. Gu, and M. J. Ostwald, "Creativity and parametric design? Comparing designer's cognitive approaches with assessed levels of creativity," *International Journal of Design Creativity and Innovation*, vol. 3, no. 2, pp. 78–94, Apr. 2015, doi: 10.1080/21650349.2014.931826.

[22] R. Yu, N. Gu, and M. Ostwald, "Comparing designers' problem-solving behavior in a parametric design environment and a geometric modeling environment," *Buildings*, vol. 3, no. 3, pp. 621–638, Sep. 2013, doi: 10.3390/buildings3030621.

[23] J. Lee, N. Gu, and A. P. Williams, "Parametric design strategies for the generation of creative designs," *International Journal of Architectural Computing*, vol. 12, no. 3, pp. 263–282, Sep. 2014, doi: 10.1260/1478-0771.12.3.263.

[24] J. Harding, S. Joyce, P. Shepherd, and C. Williams, "Thinking topologically at early stage parametric design," in *Advances in Architectural Geometry*, Paris, 2012.

[25] E. Kalkan, F. Y. Okur, and A. C. Altunışık, "Applications and usability of parametric modeling," *Journal of Construction Engineering, Management & Innovation*, vol. 1, no. 3, pp. 139–146, Oct. 2018, doi: 10.31462/jcemi.2018.03139146.

[26] N. C. Brown and C. T. Mueller, "The effect of performance feedback and optimization on the conceptual design process," in *International Association of Spatial Structures Annual Symposium*, Tokyo, Sep. 2016. [Online]. Available: https://www.researchgate.net/publication/316107726

[27] T. Wortmann and B. Tunçer, "Differentiating parametric design: Digital workflows in contemporary architecture and construction," *Des Stud*, vol. 52, pp. 173–197, Sep. 2017, doi: 10.1016/j.destud.2017.05.004.

[28] M. Stavric and O. Marina, "Parametric modeling for advanced architecture," *International Journal of Applied Mathematics and Informatics*, vol. 5, no. 1, pp. 9–16, 2011, [Online]. Available: https://www.researchgate.net/publication/285467523

[29] A. Rolvink, R. van de Straat, and J. Coenders, "Parametric structural design and beyond," *International Journal of Architectural Computing*, vol. 8, no. 3, pp. 319–336, Sep. 2010, doi: 10.1260/1478-0771.8.3.319.

[30] E. Touloupaki and T. Theodosiou, "Optimization of building form to minimize energy consumption through parametric modelling," *Procedia Environ Sci*, vol. 38, pp. 509–514, 2017, doi: 10.1016/j.proenv.2017.03.114.

[31] T. Wortmann, "Model-based optimization for architectural design: Optimizing daylight and glare in grasshopper," *Technology|Architecture + Design*, vol. 1, no. 2, pp. 176–185, Nov. 2017, doi: 10.1080/24751448.2017.1354615.

[32] Q. Liu, X. Han, Y. Yan, and J. Ren, "A parametric design method for the lighting environment of a library building based on building performance evaluation," *Energies (Basel)*, vol. 16, no. 2, p. 832, Jan. 2023, doi: 10.3390/en16020832.

[33] D. Holzer, R. Hough, and M. Burry, "Parametric design and structural optimisation for early design exploration," *International Journal of Architectural Computing*, vol. 5, no. 4, pp. 625–643, Dec. 2007, doi: 10.1260/147807707783600780.

[34] M. Tsigkari, A. Chronis, S. C. Joyce, A. Davis, S. Feng, and F. Aish, "Integrated design in the simulation process," in *Proceedings of the Symposium on Simulation for Architecture & Urban Design*, San Diego, Apr. 2013, pp. 153–162.

[35] P. Block, T. Van Mele, M. Rippman, and N. Paulson, *Beyond Bending: Reimagining Compression Shells*. Munich: Detail, 2017.

[36] J. H. Lee, M. J. Ostwald, and N. Gu, *Design Thinking: Creativity, Collaboration and Culture*. Cham, Switzerland: Springer Ebook, 2020. [Online]. Available: https://link.springer.com/book/10.1007%2F978-3-030-56558-9

[37] D. Yang, L. Wang, and G. Ji, "Optimization-assisted building design - cases study of design optimization based on real-world projects," in *the 40th Conference on Education and Research in Computer Aided Architectural Design in Europe (eCAADe 2022)*, B. Pak, G. Wurzer, and R. Stouffs, Eds., Ghent, 2022, pp. 609–618.

[38] P. Geyer and K. Beucke, "An integrative approach for using multidisciplinary design optimization in AEC," in *the International Conference on Computing in Civil and Building Engineering*, W. Tizani, Ed., 2010.

[39] K. Nielson and M. Khademi, "CoOptimise: Exploring human and machine cooperation in optimization and design," *eCAADe 25: Shock! Sharing of Computable Knowledge*. Sep. 2017.

[40] X. Liu, L. Wang, and G. Ji, "Optimization-Based Design Exploration of the Mutual Influence Between Building Massing and Façade Design," in *2022 Annual Modeling and Simulation Conference (ANNSIM)*, IEEE, Jul. 2022, pp. 487–499. doi: 10.23919/ANNSIM55834.2022.9859405.

[41] A.-T. Nguyen, S. Reiter, and P. Rigo, "A review on simulation-based optimization methods applied to building performance analysis," *Appl Energy*, vol. 113, pp. 1043–1058, Jan. 2014, doi: 10.1016/j.apenergy.2013.08.061.

[42] E. Touloupaki and T. Theodosiou, "Performance Simulation Integrated in Parametric 3D Modeling as a Method for Early Stage Design Optimization—A Review," *Energies (Basel)*, vol. 10, no. 5, p. 637, May 2017, doi: 10.3390/en10050637.

[43] N. C. Brown and C. T. Mueller, "Design for structural and energy performance of long span buildings using geometric multi-objective optimization," *Energy Build*, vol. 127, pp. 748–761, Sep. 2016, doi: 10.1016/j.enbuild.2016.05.090.

[44] J. Felkner, E. Chatzi, and T. Kotnik, "Interactive particle swarm optimization for the architectural design of truss structures," in *2013 IEEE Symposium on Computational Intelligence for Engineering Solutions (CIES)*, J. Felkner, E. Chatzi, and T. Kotnick, Eds., Singapore: IEEE, Apr. 2013, pp. 15–22. doi: 10.1109/CIES.2013.6611723.

[45] R. A. Danhaive and C. T. Mueller, "Combining parametric modeling and interactive optimization for high-performance and creative structural design.," in *Proc., IASS Annual Symp*, Madrid, Spain: International Association for Shell and Spatial Structures, 2015.

[46] L. Wang, H. Wong Nyuk, and S. Li, "Facade design optimization for naturally ventilated residential buildings in Singapore," *Energy Build*, vol. 39, no. 8, pp. 954–961, Aug. 2007, doi: 10.1016/j.enbuild.2006.10.011.

[47] L. E. Hinkle, J. Wang, and N. C. Brown, "Quantifying potential dynamic façade energy savings in early design using constrained optimization," *Build Environ*, vol. 221, p. 109265, Aug. 2022, doi: 10.1016/j.buildenv.2022.109265.

[48] D. Yang, Y. Sun, M. Turrin, P. von Buelow, and J. Paul, "Multi-objective and multidisciplinary design optimization of a large sports building envelopes: a case study," in *International Association of Shell and Spatial Structures 2015 Amsterdam Symposium: Future Visions - Computational Design*, Amsterdam, 2015, pp. 1–14.

[49] C. Stones and T. Cassidy, "Seeing and discovering: how do student designers reinterpret sketches and digital marks during graphic design ideation?," *Des Stud*, vol. 31, no. 5, pp. 439–460, Sep. 2010, doi: 10.1016/j.destud.2010.05.003.

[50] J. M. Cichocka, W. N. Browne, and E. Rodriguez, "Optimization in the architectural practice," in *22nd International Conference of the Association for Computer-Aided Architectural Design Research in Asia (CAADRIA)*, P. Janssen, P. Loh, A. Raonic, and M. A. Schnabel, Eds., Hong Kong: The Association for Computer-Aided Architectural Design Research in Asia, 2017, pp. 387–397.

[51] T. Wortmann and G. Nannicini, “Introduction to architectural design optimization,” in *City Networks*, A. Karakitsiou, A. Migdalas, S. Rassia, and P. Pardalos, Eds., Springer, 2017, pp. 259–278.

[52] L. Wilson, J. Danforth, C. C. Davila, and D. Harvey, “How to generate a thousand master plans: A framework for computational urban design,” in *SimAUD 2019*, Atlanta, Georgia, Apr. 2019.

[53] A. Stals, S. Jancart, and C. Elsen, “Parametric modeling tools in small architectural offices: Towards an adapted design process model,” *Des Stud*, vol. 72, p. 100978, Jan. 2021, doi: 10.1016/j.destud.2020.100978.

[54] R. A. Wicklund and P. M. Gollwitzer, *Symbolic Self-completion*. New Jersey: Lawrence Erlbaum Associates, Inc., 1982.

[55] R. Dou, Z. Hazari, K. Dabney, G. Sonnert, and P. Sadler, “Early informal STEM experiences and STEM identity: The importance of talking science,” *Sci Educ*, vol. 103, no. 3, pp. 623–637, May 2019, doi: 10.1002/sce.21499.

[56] M. Davis, “Distinguishing architects from engineers: A pilot study in differences Between engineers and other technologists,” in *Philosophy and Engineering*, 2009, pp. 15–30. doi: 10.1007/978-90-481-2804-4_2.

[57] D. Jonassen, J. Strobel, and C. B. Lee, “Everyday problem solving in engineering: Lessons for engineering educators,” *Journal of Engineering Education*, vol. 95, no. 2, pp. 139–151, Apr. 2006, doi: 10.1002/j.2168-9830.2006.tb00885.x.

[58] A. Saint, “Architect and Engineer: A Study in Sibling Rivalry,” Yale University Press, 2008.

[59] E. Allen, “Keynote Address,” in: D.J. Oakley, R.E. Smith (Eds.), in Proceedings of the 2006 Building Technology Educators’ Symposium, 2006.

[60] E. Allen, and W. Zalewski,. *Form and Forces: Designing Efficient, Expressive Structures*. Hoboken, New Jersey: John Wiley and Sons, 2009.

[61] A.J. Macdonald, *Structure and architecture*, Routledge, 2018.

[62] O. Tessmann, *Collaborative design procedures for architects and engineers*. Ph.D. Dissertation, Universitat Kassel, 2008.

[63] S.G. Attia, J.L.M. Hensen, L. Beltran, A. De Herde, Selection criteria for building performance simulation tools: contrasting architects' and engineers' needs, *J Build Performance Simulation*. 5 (2012) 155–169.

[64] M. A. Schnabel, "Learning parametric designing," in *Industrial Engineering*, IGI Global, 2013, pp. 197–210. doi: 10.4018/978-1-4666-1945-6.ch013.

[65] K. Romaniak and S. Filipowski, "Parametric design in the education of architecture students," *World Transaction on Engineering and Technology Education*, vol. 16, no. 4, pp. 386–391, 2018.

[66] A. P. Ponzio, M. G. Gonzaga, M. P. de Castro, A. Vale, U. M. Bruscato, and W. Mog, "Parametric design learning strategies in the context of architectural design remote teaching," in *SIGRADI 2021 Designing Possibilities Ubiquitous Conference*, 2021, pp. 1077–1088.

[67] C. J. de Oliveira, L. O. Steffen, C. A. de M. Vasconcellos, and P. F. Sanchez, "Structural topology optimization as a teaching tool in the architecture," *Revista de Ensino de Engenharia*, vol. 37, no. 3, 2018, doi: 10.5935/2236-0158.20180039.

[68] N. C. Brown and S. Bunt, "Optimization tools as a platform for latent qualitative design education of technical designers," in *National Conference on Beginning Design Students*, S. Burns and Kristin Barry, Eds., 2022.

[69] Z. Akbar, G. Ron, and T. Wortmann, "Democratizing the designer's toolbox," in *eCAADe 41 Digital Design Reconsidered*, Graz, Austria, 2023, pp. 41–50.

[70] Z. Tian, X. Zhang, X. Jin, X. Zhou, B. Si, and X. Shi, "Towards adoption of building energy simulation and optimization for passive building design: A survey and a review," *Energy Build*, vol. 158, pp. 1306–1316, Jan. 2018, doi: 10.1016/j.enbuild.2017.11.022.

[71] W. Peng, "Teaching reform and optimization design of architectural performance course," *International Journal of Social Science and Education Research*, vol. 4, no. 9, pp. 48–52, 2021.

[72] S. Ahmed, K. M. Wallace, and L. T. Blessing, “Understanding the differences between how novice and experienced designers approach design tasks,” *Res Eng Des*, vol. 14, no. 1, pp. 1–11, Feb. 2003, doi: 10.1007/s00163-002-0023-z.

[73] B. Lawson and K. Dorst, “Acquiring design expertise,” in *Computational and Cognitive Models of Creative Design VI: Reprints of International Conference of Computational and Cognitive Models of Creative Design*, J. Gero and M. Lou Maher, Eds., Heron Island, Australia: Key Centre of Design Computing and Cognition, Dec. 2005.

[74] M. Kavakli and J. S. Gero, “Strategic knowledge differences between an expert and a novice designer,” in *Human Behavior in Design*, U. Lindemann, Ed., Berlin, Heidelberg: Springer Berlin Heidelberg, 2003, pp. 42–52. doi: 10.1007/978-3-662-07811-2.

[75] N. Cross, “Expertise in design: an overview,” *Des Stud*, vol. 25, no. 5, pp. 427–441, Sep. 2004, doi: 10.1016/j.destud.2004.06.002.

[76] J. Sweller, “Cognitive load during problem solving: Effects on learning,” *Cogn Sci*, vol. 12, no. 2, pp. 257–285, Jun. 1988, doi: 10.1016/0364-0213(88)90023-7.

[77] G. H. Bower, “Cognitive psychology: an introduction,” in *Handbook of learning and cognitive processes: Introduction to concepts and issues*, W. K. Estes, Ed., Hillsdale, New Jersey: Erlbaum, 1975, pp. 25–80.

[78] M. Chi, R. Glaser, and E. Rees, “Expertise in problem solving,” in *Advances in the psychology of human intelligence*, R. Sternberg, Ed., Hillsdale, New Jersey: Erlbaum, 1982, pp. 7–75.

[79] T. Dissaux and S. Jancart, “Impact of cognitive load associated with learning and using parametric tools in architectural design,” in *XIX Congreso Internacional de Expresión Gráfica Arquitectónica, junio 2022*, Universidad Politécnica de Cartagena, 2022, pp. 643–646. doi: 10.31428/10317/11415.

[80] F. G. W. C. Paas and J. J. G. Van Merriënboer, “The Efficiency of Instructional Conditions: An Approach to Combine Mental Effort and Performance Measures,” *Human Factors: The Journal*

*of the Human Factors and Ergonomics Society*, vol. 35, no. 4, pp. 737–743, Dec. 1993, doi: 10.1177/001872089303500412.

[81] J. Sweller, P. Ayres, and S. Kalyuga, "Measuring Cognitive Load," in *Cognitive Load Theory*, New York, NY: Springer New York, 2011, pp. 71–85. doi: 10.1007/978-1-4419-8126-4_6.

[82] P. A. Kirschner, "Cognitive load theory: implications of cognitive load theory on the design of learning," *Learn Instr*, vol. 12, no. 1, pp. 1–10, Feb. 2002, doi: 10.1016/S0959-4752(01)00014-7.

[83] S. Tan, "Towards an integrative approach to researching design expertise," *Des Stud*, vol. 74, p. 101017, May 2021, doi: 10.1016/j.destud.2021.101017.

[84] J. H. Lee, M. J. Ostwald, and N. Gu, "Introduction: exploring design thinking," in *Design Thinking: Creativity, Collaboration and Culture*, Springer EBook, 2020, pp. 1–32.

[85] J. S. Gero and U. Kannengiesser, "The situated function–behaviour–structure framework," *Des Stud*, vol. 25, no. 4, pp. 373–391, Jul. 2004, doi: 10.1016/j.destud.2003.10.010.

[86] S. P. Marshall, "The Index of Cognitive Activity: measuring cognitive workload," in *Proceedings of the IEEE 7th Conference on Human Factors and Power Plants*, IEEE, 2002, pp. 7-5-7–9. doi: 10.1109/HFPP.2002.1042860.

# Chapter 3

## Assessing Pre-Design Student Perceptions

Work in this chapter was originally published as S. Bunt, L Hinkle, A. Walton, N. C. Brown, “Relationship between High School STEM Self-Competency and Behavior in a Parametric Building Design Activity,” in *2023 ASEE Annual Conference & Exposition*, Baltimore, Maryland: American Society of Engineering Education, June 25, 2023. The version presented in this document is expended with more detail.

### Abstract

Building designers receive discipline-specific education which prepares them to address distinct design goals, but they may struggle to address criteria not considered part of their profession based on their disciplinary identity. In STEM subjects, such as engineering, high school students’ perception of their own competency is positively related to their performance. Although this is beneficial for engineering design, it is unclear how students who identify strongly with STEM prior to professional training may account for non-STEM design objectives compared to STEM-related criteria. This research considers how pre-design students’ STEM self-competency can predict their behavior when responding to a building design task with technical and non-technical goals. A study was conducted which asked high school students about their STEM competency and instructed them to develop a conceptual skyscraper design in an age-accessible, digital design environment. The design tool contained a parametric model which provided visual and performance feedback about energy use, daylight, and cost as the students changed skyscraper variables. Students with higher STEM self-competency (SC) selected higher-

performing designs, viewed more design iterations, and ranked the building's appearance as their lowest priority. These results inform future design educators about student outlook prior to any professional training and reveal potential limitations in student approaches to multidisciplinary building design tasks.

## 3.1 Introduction

Aspects of college students' career choices are influenced by how closely they identify with the subject matter, particularly in STEM fields [1], which may influence them to behave in a way they feel is emblematic of that profession [2]. This is relevant to majors such as engineering and architecture that require collaborative design expertise but can often define and approach their design goals differently [3]. Since design is a complex, challenging endeavor that requires both skillsets, educators in each profession may seek to avoid rigid self-classifications among students. For example, engineering majors can benefit from understanding they can be creative, synthetic thinkers, and architects can learn to incorporate calculations more productively during design.

Recent efforts in engineering education have sought to develop such crossover skills among engineers, including problem-based learning [4], [5] and integrated design studios with architecture students. As an approach to multi-disciplinary design, emerging parametric modeling tools, which can provide both geometric and numeric feedback, have been shown to improve design performance [6]–[8] and are a viable environment for design decision making [9]. It is unclear, though, how the disciplines approach these tools differently because of their varying professional training, outlook, and experience. In addition, little is known about how students may use these tools based on their design aptitudes at various stages of development. It is likely that as students gain training and eventual experience as designers, their approach to using a computational tool will increase in similarity to experts. This could be partially due to improving aptitudes, but it may also be influenced by a learned professional outlook or orientation. However, student perceptions of creativity and technical fields may emerge and even solidify prior to starting college coursework [10]. College-level instructors may thus encounter prior biases when formally teaching design to students for the first time.

Before entering secondary education, students are not yet characterized by an associated future profession—they are not yet “engineering” students. Instead, as the acronym STEM (Science, Technology, Engineering, and Math) has become a widespread term in education to strengthen and grow student awareness of these subjects, strong STEM associations may influence students’ thinking about design in unintended ways. While positive exposure to STEM fields can lead to more participation in STEM activities, students may approach design tasks with a narrower, STEM-oriented focus, rather than a comprehensive solution that includes non-technical considerations. Previous research has shown that a student’s self-perception of their performance in STEM subjects can positively predict their actual STEM performance [1], but less is known about how STEM-competent students navigate non-STEM goals, particularly if they identify more exclusively within STEM fields.

In response, this research examines how high school students’ self-competency in STEM (STEM SC) relates to their design performance, exploration, and priorities when responding to a parametric building design activity. Three research questions are asked:

**RQ1: How does student STEM SC relate to their design performance in parametric building design?** In this study, “design performance” refers to the ability of students to generate solutions that have good performance in quantitative metrics such as low energy usage. Previous research shows that student self-efficacy and performance are positively related both outside of STEM [11] and in STEM [12]. However, this study evaluates performance specifically in a building design exercise with quantitative goals that are simulated within a parametric design tool. This relationship can reflect potential student effectiveness in technical building design, but it does not fully reflect student behavior. The extent of their exploration with the design space can suggest their intended engagement of the task, prompting the second research question:

**RQ2: How does high school student STEM SC relate to their design exploration?** Engaging with many possible solutions can reflect a designer's intent and suggest a level of interest in the material. Hazari acknowledges interest as a measure for identity in STEM subjects [13], and iterative exploration is fundamental to problem-solving [14]. Yet building design tasks often have many goals which may capture designers' interests differently, as they may prioritize some criteria over others. The third research question asks:

**RQ3: How does student STEM SC relate to the design criteria that they value?** In building design, rarely is a single design consideration isolated from holistic problem solving. Multi-disciplinary problem-solving is necessary but may be limited if a student with a strong STEM SC does not value goals that are not considered part of traditional STEM criteria, such as aspects of building appearance.

To answer these questions, a study was conducted at a high school in the Northeastern United States that asked students about their relationship with STEM both directly and indirectly. They then respond to a building design task with three technical criteria and one qualitative criterion. Students worked in a readily accessible parametric modeling tool that collected information about their exploration and performance, while a survey recorded their priorities when designing. Design performance was assessed using simplified performance simulations for building cost, energy use, and artificial light required. These relative metrics were presented back to students during their exploration, allowing them to prioritize between quantitative and qualitative objectives. The resulting correlations can prompt educators to incorporate more intentional multi-disciplinary thinking in K-12 curriculum to better prepare students for complex problems if they pursue design professions.

## 3.2 Background

Considerable research has already been conducted on engineering creative thinking and STEM education. However, less is known about how students' natural approaches to a design task might be influenced by STEM self-competency before initial exposure to formal design training of any type. We use the term self-competency to describe students' perception of what they can accomplish with their abilities, following Susan Harter [15], but applying the concept to more specific academic subdomains. In addition, theoretical frameworks such as expectancy-value theory support that students' expectancy to be able to perform a task, combined with students' value of a task, can predict outcomes of engagement and achievement [16], [17]. Assessing self-competency also allows us to engage with literature that considers performance-competency as an indicator for identity, which is central to our research, since professional identify formation may influence design behavior.

Further, we consider "exclusive" self-competency by asking students about their abilities in STEM versus non-STEM courses on a continuum. While students may be good at both types of subjects, American architecture and engineering programs usually enforce a binary—with few exceptions, students will largely graduate with professional training and a degree in only one or the other. In this context, the goal is to understand how far a student may be identifying in either direction prior to receiving any formal design training. We thus begin the review with what has been established about engineers and architects' design behavior, before working backwards to how these behaviors may have been influenced earlier in education.

### 3.2.1 Design Thinking in Engineering and Architecture

Effective building design requires both technical and experiential considerations, which are addressed by engineers and architects through their disciplinary expertise. Although their distinctions may be less clear with newer digital tools, it has been observed that the professions approach design differently in pursuit of their disciplinary goals [3] and receive distinct professional training. This training is useful when addressing their expert tasks but may cause conflict when addressing multidisciplinary problems. Engineering students mostly follow outcome-based strategies [18] but can struggle to solve open-ended or ill-defined tasks [19], especially if their curriculum has not adequately prepared them for these problem types that occur in the workplace. On the other hand, architecture students are strong at creative thinking, but may shy away from rigorous quantitative analysis [20]. Thus, university-level instructors may need to consider how they promote potential design orientations by the tasks they assign and provide design environments that require diverse approaches to problem-solving.

### 3.2.2 Parametric Thinking and Modeling in Design

One context in which design creativity might be stimulated is parametric modeling, which allows designers to generate and consider a wide range of potential solutions. In parametric modeling, variables control characteristics of a building such as height and window size, while performance objectives can be calculated rapidly, sometimes even providing live design feedback depending on the scale of the problem. Design solutions can then be explored by both architects and engineers for qualitative and quantitative properties. These tools have been used in previous research as a viable environment for design decision making [6], [7], [21], [22]. Professionals have also used parametric modelling in practice when iterating design performance analysis, such as ARUP [23] and Foster + Partners [24]. In addition, computational thinking has been incorporated in student education [25], and parametric models have been used as teaching tools to improve learning [26] and support STEM education [27], [28].

Thus, even though exploration in a parametric design tool does not represent a comprehensive design process from start to finish, it is intuitive enough for even K-12 students and can capture some design behavior. Understanding how pre-design students use these tools prior to professional training can inform strategies for their disciplinary education, but grade school students may not have a clear understanding of what is expected of building design fields. A more relatable, generalizable proxy is needed to measure their potential success and identity in building design professions.

### 3.2.3 The Influence of STEM

In the last two decades, a strong emphasis on STEM subjects has empowered young thinkers, given agency to groups underrepresented in the fields [29], and accentuated STEM recognition early in grade school. Incorporating STEM concepts early can have potential benefits, such as fostering student positive perception of STEM values [30] and increasing interest in STEM related fields for future careers [31], [32], but it could also contribute to challenges in cross-disciplinary problem solving. Children begin to identify their career interests and aspirations as early as elementary school [33]–[35] and greater STEM identity leads students to pursue STEM fields in their career [1]. However, there are also negative stereotypes surrounding STEM, such as it being less creative and boring [10], which can have negative impacts on student pursuit of STEM professions and STEM self-competency. These stereotypes may be influenced by real factors such as the fact that performance in math, often perceived as less creative, is a reoccurring predictor for STEM pursuits when compared to other subjects and influential variables [36], [37]. For pre-engineering students who perform well at math, many may come to college thinking that as a "STEM student" they are only good at solving numerical problems, while pre-architecture students may have negative associations with STEM and be intimidated by calculations. Therefore, how a student perceives STEM can influence their building design pursuits.

Discerning how students think of STEM relies on various social identity theories [38]–[40]. STEM identity has been defined as how well individuals see themselves as an accepted member of STEM [41] or if they think of themselves as a scientist, technology user, engineer, or mathematician [42]. Subdividing identity into three interrelated components, Carlone and Johnson [43] defined STEM identity as performance (demonstrate activity), competency (knowledgeable in activity), and recognition (credible by others). Accounting for a person's sense of choice in self-perception, Hazari [13] built on Carlone and Johnson to add interest to STEM identity. Hazari also combined performance with competency to measure an individual's belief about their own abilities to perform and understand a STEM subject. However, both Carlone and Johnson and Hazari focused on only science subjects in STEM. To understand identity more broadly, Dou and Chian [44] surveyed all STEM fields individually, relying on performance-competency as an indicator for identity along with recognition and interest. Their research acknowledged that recognition and interest can be difficult to define depending on a student's understanding of what is involved in STEM fields and students are not yet in career positions for professional recognition. As a result, performance-competency can capture both ability and perception of efficacy, and it is a predictor for better performance [11]. Additionally, greater STEM self-efficacy has been shown to predict improved STEM performance [1].

While some studies have separated engineering from other STEM fields for more specific understanding of the profession [45], [46], this paper also considers differences between engineers and architects, which both contribute to building design. STEM has always included "engineering," but "architecture" was not officially recognized by Congress as a STEM subject until 2019 [47]. It is unclear if the general population is aware of its recent inclusion. Nevertheless, there is a call for more systematic research of how STEM and design relate in education [48], [49].

Based on gaps in the research, this paper examines if STEM SC can predict pre-design student performance and engagement in a building parametric design tool, and how the students prioritize different criteria. How students use parametric tools prior to formal training is important because this is an emerging environment for multi-disciplinary building design.

## 3.3 Methods

This paper studies STEM SC and design behavior in an intuitive, age-appropriate design exercise facilitated in an online computational design tool.

### 3.3.1 Participants

The IRB approved study was conducted at a public high school in the Northeastern US with 107 ninth and tenth grade participants. The overall high school population is 71.4% white with a total minority enrollment of 28.6%. The school performs between 17-28% above average in the state's annual Mathematics, Reading, and Science proficiency exams with a 91% graduation rate. Of the participants, 50 were boys, 53 were girls, 3 were gender non-conforming, and 1 preferred not to answer. All students were enrolled in the Environmental Sciences or Chemistry class at the high school in either honors or non-honors tracks, based on the school's distinctions of academic rigor. Of the participants, 67 were honors students and 40 were not.

### 3.3.2 Design Session

The study protocol was conducted during the school day and lasted 1 hour and 15 minutes. The activity was voluntary and parental consent was obtained. An alternative activity was provided for students who chose not to participate. Students were not graded on their performance, and the activity did not relate to their coursework. The study design included an intake survey, two introduction videos, a design session, and a final survey (Figure 3-1). The intake survey captured their demographics and STEM SCs; the videos introduced skyscrapers and the design task; the design tool used during the design session recorded the students' design exploration and final design performance; and the final survey asked the students which of the design criteria they prioritized when designing.

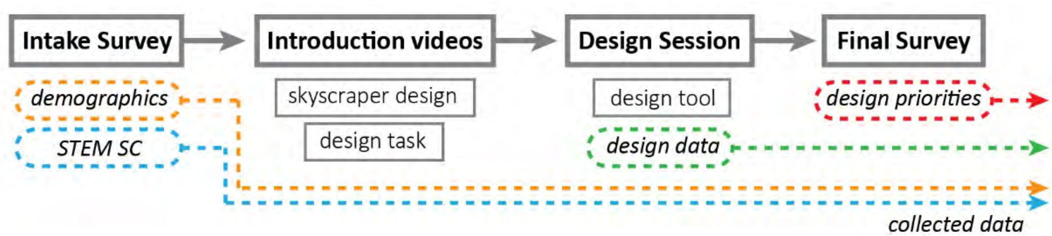


Figure **3-1**. A summary of the protocol during the design sessions.

#### *3.3.2.1 Preliminary Material*

At the beginning of the study, students completed a survey which collected demographic information and asked about their self-competency in STEM. In this survey, the acronym for STEM was spelled out so the students were aware of which subjects were included in the category of STEM. Self-competency was isolated from other dimensions of STEM identity to narrow potential variations in STEM biases, which can occur with recognition and interest. The participants may not understand architecture or engineering professions specifically to determine their personal interests, nor have they yet entered the professions to be recognized for their efforts. The focus of the research was not disclosed to the students to avoid influencing their perceptions of the questions and research task. They were asked “Which statement most accurately describes you?” and responded by moving a slider between “I am strong in STEM related subjects” and “I am strong in subjects not considered part of STEM,” with the slider starting in the middle. When recording their STEM Self-Competency (STEM SC), it was important to not bias student responses with leading phrases that would prompt undue associations. The full pre- and post-survey is provided in Appendix A.

We followed a similar question structure from a previous study of STEM competency which provided statements such as “I think I am very good at: Figuring out science activities,” and students responded with how closely they agreed [50]. While agreement style of survey questions are legitimate forms of data collection, in the context of our study, this type of question may suggest a “yes” response as affirmative, while a “no” may be viewed as negative. Therefore, our question about STEM SC was intentionally phrased in a neutral way to enable students to emphasize strengths in different areas. Self-competency in STEM is not inherently exclusive and if a student felt like they identified with both statements, they could place the slider in between the options. In answering the third research question, students who view themselves more exclusively in a STEM context may be limited in their approaches to consider multidisciplinary design criteria. In addition, providing a concise question as opposed to a multi-faceted questionnaire also avoids student survey fatigue as a part of the study session. Although the slider was not presented numerically to students, results were captured in discrete settings.

The students were shown an 8-minute video made for the study that presented skyscraper design ideas and focused on building characteristics of energy, daylighting, cost, and appearance. The video advised that skyscrapers are advantageous when they are larger because that increases the square footage, but that increases costs. A building with a larger surface area also allows for more natural daylight through windows, reducing the need for artificial light during working hours, but this larger building will also use more energy. Participants were shown ten examples of built skyscrapers, illustrating a range of form and color, to explain how appearance is also an important part of skyscraper design to give a city or building tenant an identity.

#### *3.3.2.2 Design Task*

The design task asked students to present a solution for a new skyscraper in Austin, TX that would serve as a high-performance office building for Google. To help focus their design efforts, the students were advised to minimize three Objective Metrics: energy use, artificial light, and cost. They were also provided the freedom to prioritize between each. The objectives were calculated by multiplying the normalized values of the variables by a coefficient, based on the variables' approximate proportional impact on the objective, and adding the results. A table explaining how the variables were related to calculate the performance metrics is provided in Appendix B. The quantitative goals had inverse relationships such that no perfect design exists where all three criteria can be minimized. They were also told that Google wanted a visually appealing design as a non-technical design goal.

#### *3.3.2.3 Design Tool*

A digital tool was developed that allowed the students to work in 3D modeling space without previous modeling skills and provided the students with live performance feedback about their designs. The tool also collected data about the students' design behavior and performance of their final design. Participants used a custom website created for the study using a file hosting platform called Shapediver [51]. The Shapediver API was used to embed a pre-built Grasshopper file which defines 3D geometry, variables, and design performance values. The skyscraper model with surrounding site context had eleven variables and provided quantitative feedback for the three objectives through a dynamic bar graph which changed with the variables. Seven of the variables edited the geometry of the skyscraper and four of the variables changed aspects of the exterior enclosure panels.

All variables impacted at least one performance metric, except for the color of the panels, which related only to the buildings' appearance. The underlying values of the performance bars, not shown to the users, were calculated based on the intuitive behavior of a building with similar features. These simplified relationships prevented the need for running full simulation programs to supply quantitative feedback, avoiding design fatigue. The quantitative objectives have different dimensions of measurement and were thus normalized and presented in graphical form for easy student interpretation. The students' goal was to minimize the objectives, but since the objectives have inverse relationships, no solution minimized or maximized all. An overview of the tool is provided in Figure 3-2, showing the website interface with the skyscraper model and performance bars, along with the design variables. As the students worked in the tool, the website collected data about how often they changed each variable and recorded the final objective values at the end of the session. The final objective values were averaged to measure the Objective Performance.

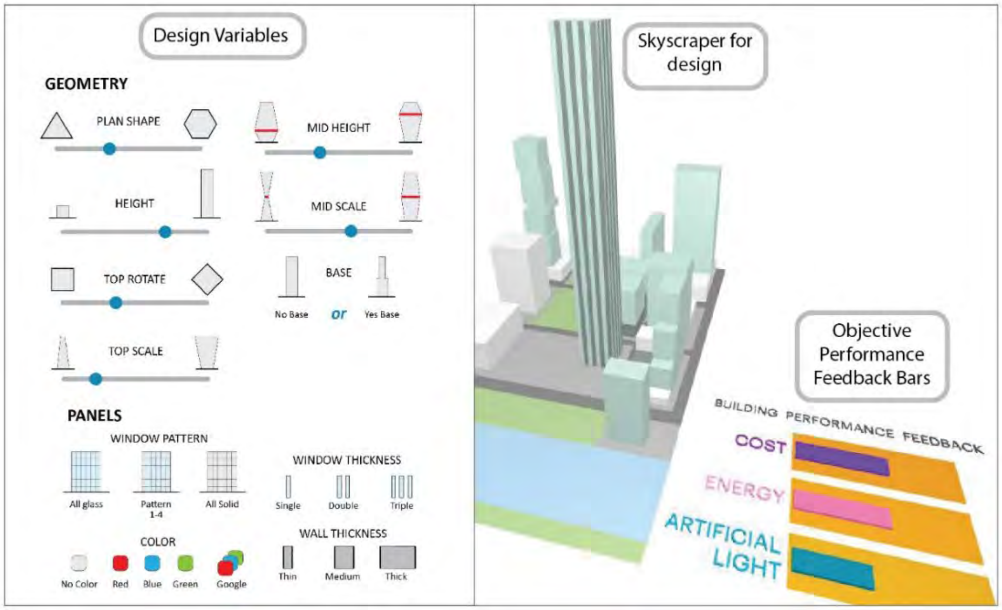


Figure **3-2**. Sample of the design tool showing the 11 variables and the modeling space with the skyscraper and performance feedback bars.

As the students worked in the tool, the website collected data about how often they changed each variable and recorded the final objective values at the end of the session. The final objective values were averaged to measure the Objective Performance.

### 3.3.3 Assessment

This study focused on STEM Self-competency and the three Objective Metrics as proxies for student design behavior because of their relevancy to building design thinking and the population of interest. Linear regression models of the study's Objective Metrics vs STEM SC were used to determine if STEM SC is a predictor for the Objective Metrics. Design performance was determined by how well the students minimized the task's design criteria. STEM design performance is a part of STEM identity [43] and is a proxy of quality in creativity for the SVS and CAT methods. The number of design iterations can also positively reflect model engagement since iterative exploration is considered intrinsic to creative problem-solving [14] and can also account for a student's interest in the subject material. Prioritization of objectives, particularly "appearance" as a non-STEM goal, was measured directly through a survey. Collectively, these assessments suggest how pre-design student perception can predict their design behavior in the parametric building tool and incorporate multi-disciplinary design in the future.

### 3.4 Results

A sample of final design screenshots is shown in Figure 3-3. Although this study did not investigate visual performance of the students' designs, the samples are presented to show the range of visual solutions, by color, shape, and window patterning, that the students developed in the parametric space.

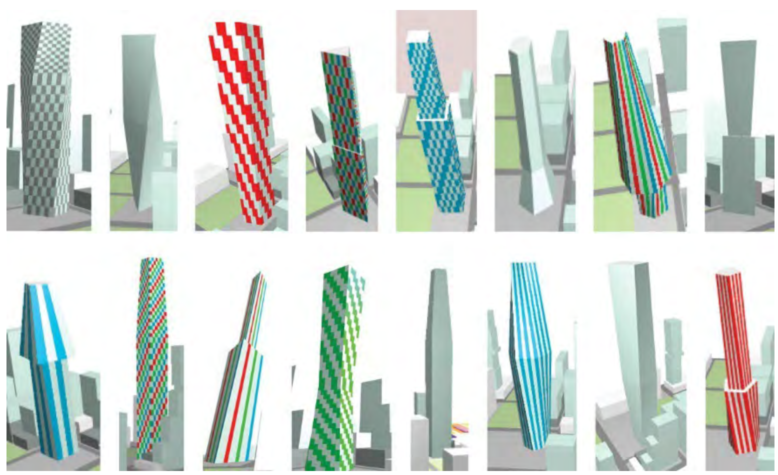

Figure **3-3**. A sample of 16 final designs provided by the students.

Figure 3-4 shows the distribution of STEM SC of the students where 0 indicates that the students reported more exclusive strong performance in STEM subjects and conversely 10 indicates that the students reported strong in subjects that are not considered part of STEM. The histogram of students' STEM SC leans slightly towards STEM related subjects with a median value of 4 and a mean of 4.45. A normal, centered distribution was not expected since STEM SC is not necessarily well distributed across all populations, and the study was conducted in an Environmental Science class.

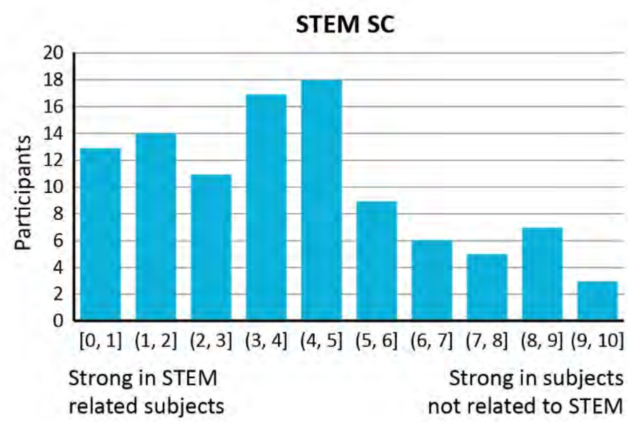


Figure **3-4**. Histogram distribution of the students STEM SC.

For the design performance, exploration, and appearance rank datasets, simple linear regression analysis was used to examine the linear relationship between the variables and STEM SC using the statistics tool Minitab. The Anderson-Darling normality test verified that the data was normally distributed ($p=0.0248$ for performance, $p=0.026$ for iterations, and $p<0.005$ for appearance rank at a $\alpha=0.05$ level of significance). Distribution plots of the datasets were visually inspected for outlier data and none were identified.

### 3.4.1 Design Performance and STEM SC

Because the goal of the design task was to minimize the objectives, a larger Objective Performance value indicated a poorer performing design, where a smaller Objective Performance was desired. Figure 3-5 shows a histogram of the Objective Performance values and a plot of STEM SC and Objective Performance. The p-value for the Regression Analysis of students' STEM SC and Objective Performance is $p=0.001$, so there is sufficient evidence at the $\alpha=0.05$ level to conclude that STEM SC can predict student performance. The left end of the x-axis indicates students who identified more closely with STEM and the right are those who identified more with non-STEM subjects. Students who associated themselves more closely with STEM subjects had quantitatively better performing designs.

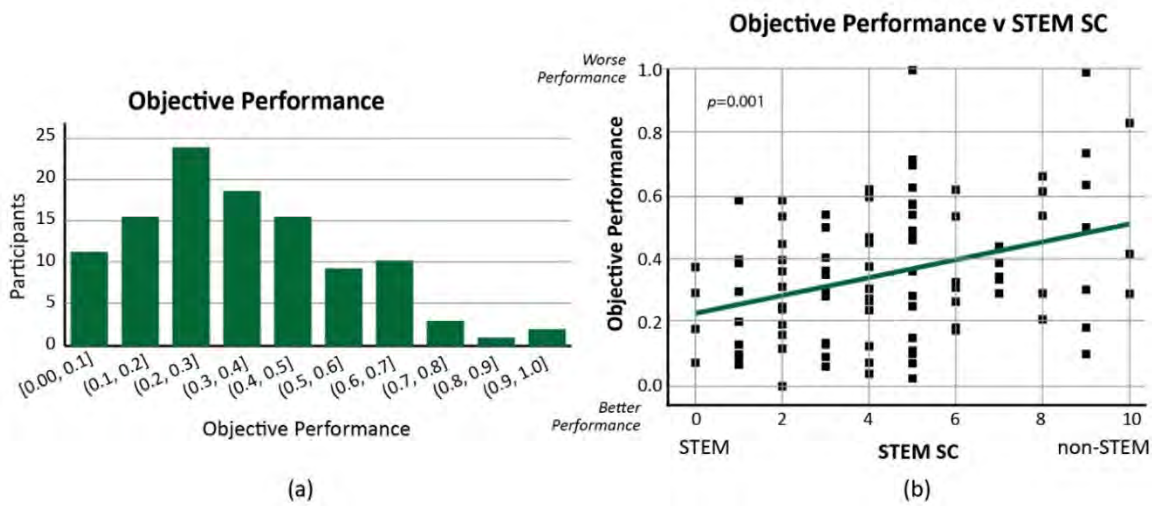


Figure **3-5**. (a) the distribution of Objective Performance values and (b) a plot of Design Performance v STEM SC, showing the regression line of the data.

### 3.4.2 Design Exploration and STEM SC

This research is also interested in understanding the relationship between STEM SC and student exploration in the parametric design tool. Figure 3-6 shows the distribution of iterations, with the fewest number being 8 and the greatest being 259, and a plot of STEM SC versus Iterations. The p-value for the regression analysis of students' STEM SC and Iterations is p=0.008, so there is sufficient evidence at the α=0.05 level to conclude that STEM SC can predict the number of iterations students considered in the design task. The left end of the x-axis indicates students who identified more closely with STEM and the right are those who identified more with non-STEM subjects. From the regression line, closer STEM identifying students explored more iterations.

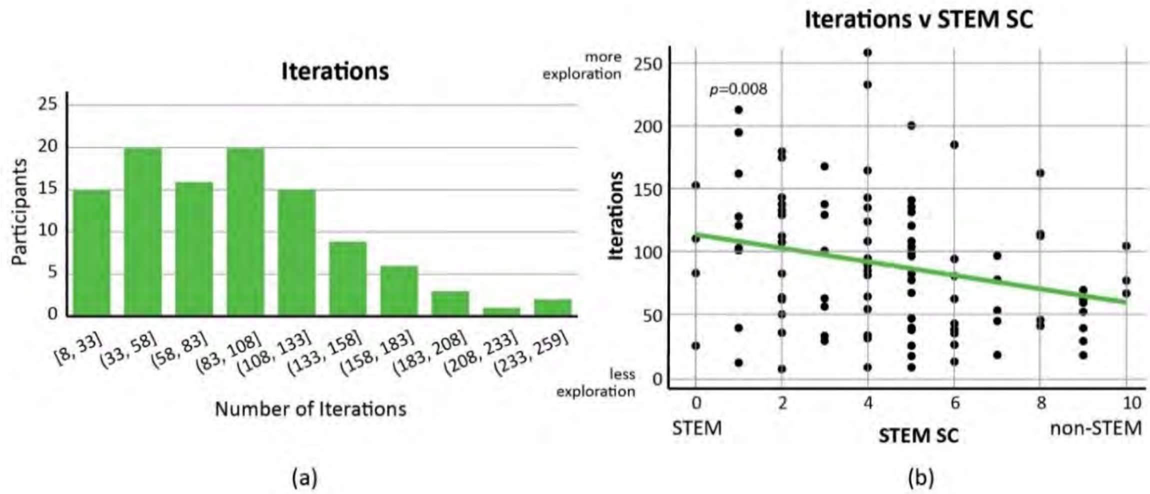


Figure **3-6**. (a) the distribution of iterations and (b) a plot of iterations v STEM SC, showing the regression line of the data.

### 3.4.3 Design Focus and STEM SC

How the students ranked criteria in order of importance was also recorded. Figure 3-7(a) shows the number of students who ranked each criterion by priority. A rank of 1 is the highest rank while 4 is the lowest. While a greater number of students ranked "appearance" as their most important criterion compared to the other criteria, "appearance" was also the lowest priority for a larger number of participants. Figure 7(b) shows a plot of STEM SC to appearance rank with the fitted regression line and the p-value of the Regression Analysis. With a p-value of p=0.062, STEM SC does not predict Appearance rank; adjusting to a α =0.10 level would indicate significant prediction. In the context of this research, it is worth considering the positive relationship between higher STEM SC and ranking appearance as a lower priority.

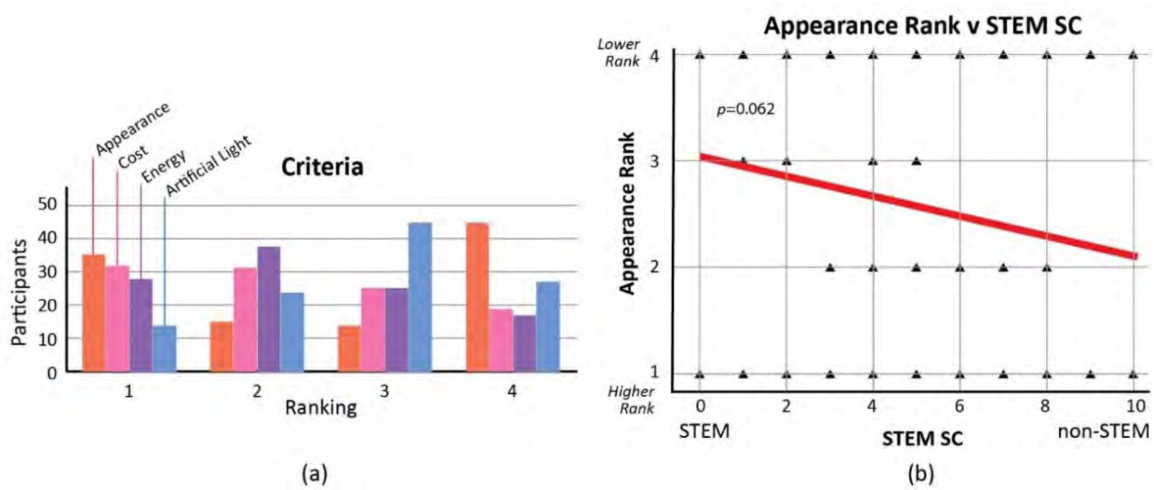


Figure **3-7**. (a) the number of participants who ranked each criterion and (b) the fitted line plot of the regression analysis for Appearance Rank v STEM SC.

### 3.4.4 Variables for Future Consideration: Gender and Honors Courses

Although they are not the main focus of this study, there has been considerable recent interest in how STEM identity relates to both gender [38], [52] and participation in honors-level courses [53]. In this section we provide preliminary consideration of these factors as they may complicate our narrative. However, the intention here is to stimulate further discussion and research rather than present new claims. Excluding the small number of alternative responses, the p-value for the Pearson Correlation between Class Type and Gender was p=0.215, which can be considered nearly uncorrelated, so we investigated the variables separately without concern for collinearity between the groups.

Linear Regressions of the variables were run for each of the study's objective metric on STEM SC for Class Type and Gender. Table 3-1 shows each of the p-values for each regression. Values that are significant at a $\alpha$=0.10 level of significance are bolded. For Honors students and Boys, their STEM SC was significant in predicting their Objective Metric, while STEM SC was not a predictor of the Non-honors students and Girls.

Table **3-1**. P-values of linear regression analysis of the study's Objective Metrics vs STEM SC, with values of significance in bold.

| | Iterations | Objective Performance | Appearance Rank |
|---|---|---|---|
| Honors | **0.005** | **0.002** | **0.085** |
| Non-honors | 0.971 | 0.239 | 0.794 |
| Boys | **0.005** | **0.000** | **0.098** |
| Girls | 0.411 | 0.257 | 0.214 |

## 3.5 Discussion

Overall, the findings suggest that more exclusive self-competency in STEM does relate positively to performance and model exploration in a parametric building tool while designing, which is advantageous if these students pursue STEM or building engineering careers. However, the study suggests that strong STEM SC could bias their ability to value qualities not considered part of STEM, leading to challenges in multi-disciplinary problem solving later in their education or careers. Examining the results by research question describes the relationship in more detail.

RQ1: How does student STEM SC relate to design performance in parametric building design? Students who expressed greater exclusive self-competency with STEM developed better performing designs, based on the tasks three quantitative criteria. It was expected that students who had greater STEM SC would navigate the technical objectives better than Non-STEM SC students, however, it was possible that the parametric building modeling tool would prompt different results in a new design space. It is necessary to also consider to what extent the students engaged with the tool.

RQ2: How does student STEM SC relate to their design exploration? The students who identified with greater STEM SC considered a greater number of iterations within the design space. Creating more iterations can reflect greater interest in the activity, as students may iterate while divergently exploring the design space to generate and consider very different options. If the number of design iterations did not vary by STEM SC, it could be that the design tool limited creativity or that the tool or task were not responsive to STEM identity. However, the students' STEM SC did predict interaction exploration indicative of engaged, creative problem-solving. It is worth noting that creating more iterations alone does not fully capture the students' response to the design task and their perception of non-technical goals, as they might have also iterated repeatedly on only slightly different design outcomes seeking the best possible design.

RQ3: How does student STEM SC relate to the design criteria that they value? Student STEM SC did predict "appearance" rank at a $\alpha = 0.10$ level of significance, as students with strong STEM SC ranked it a lower priority compared to the other criteria. This inverse relationship can suggest students with a greater STEM SC may not value visual architectural goals as highly as quantitative goals. This could be a barrier to cross-disciplinary thinking in their professional pursuits.

These conclusions can inform how K-12 educators approach presenting STEM topics. As expected, students who identified closer to STEM had better performing technical designs, but they also ranked "appearance" lower on their priorities. If the STEM-identifying students pursue careers in building design, they may struggle to incorporate non-technical goals in their design. Interdisciplinary design can be challenging to achieve [54] and research has shown that engineers can sometimes struggle to understand other viewpoints, but difficulty with multidisciplinary design is not ubiquitous to all engineers [55]. As observed in this study, the more exclusive STEM-identifying students created more iterations, which indicates greater engagement and may also show an interest in design exploration. For educators, concepts of STEM should be introduced in the context of other dimensions of design so that students can think in a multi-disciplinary way. A summary of the results is shown in Figure 3-8.

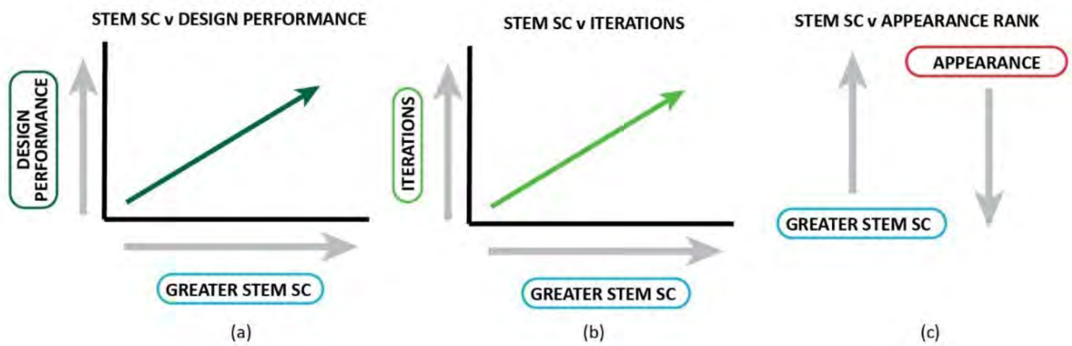


Figure **3-8**. Graphic summary of the results, with STEM SC relationship to (a) design performance, (b) iterations, and (c) appearance rank.

There are several limitations and areas for future work. While this paper focuses on relationships between STEM SC and various characteristics of design behavior, it does not exhaustively consider additional variables that may influence STEM identity in the first place. As shown in our dataset, gender and participation in Honors courses may have even stronger correlations with our Objective Metrics than STEM SC, and there are statistically significant differences in behavior when comparing populations with these characteristics. In addition, the students' enjoyment, as an extension of interest, in responding to the building design task was shown in our dataset and did not predict our Objective Metrics. Such variables likely influence both STEM SC, tool usage, and design behavior in complex ways, but they are left for future study. This paper also relies on a single continuum question to evaluate "exclusive" STEM SC. Future work can incorporate additional assessments of self-competency and/or self-efficacy while determining how they relate to design behavior. Design behavior could likewise be evaluated for different building types and other variables.

### 3.6 Conclusion

This paper presents a design study which investigated how high school student self-competency in STEM relates to design behavior in a parametric building tool. As parametric tools are increasingly used in building design fields, understanding how pre-students navigate parametric spaces is valuable in improving their education as future designers since these tools can challenge them to consider multidisciplinary criteria. The study used a parametric skyscraper design task to collect information about the students' design activity. While a different task may elicit different results based on students' interests, aspects of skyscraper design are reoccurring challenges for architects and engineers, requiring synthesis between technical and experiential design goals. In this study, the students who reported greater self-confidence with STEM subjects developed better performing designs and explored more iterations, but they also ranked "appearance" as a lower priority. These results suggest that varied design approaches that are eventually interpreted as disciplinary differences might seem natural before any formal design training occurs. They also inform educators about gaps in expected student performance in parametric tools and suggest that pre-designer education should emphasize multidisciplinary problem-solving to avoid narrowing student competency for those interested in design professions.

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## References

[1] R. Dou, Z. Hazari, K. Dabney, G. Sonnert, and P. Sadler, "Early informal STEM experiences and STEM identity: The importance of talking science," *Sci. Educ.*, vol. 103, no. 3, pp. 623–637, May 2019, doi: 10.1002/sce.21499.

[2] R. A. Wicklund and P. M. Gollwitzer, *Symbolic Self-completion*. New Jersey: Lawrence Erlbaum Associates, Inc., 1982.

[3] N. Cross and N. Roozenburg, “Modelling the design process in engineering and in architecture,” *J. Eng. Des*., vol. 3, no. 4, pp. 325–337, Jan. 1992, doi: 10.1080/09544829208914765.

[4] M. Lehmann, P. Christensen, X. Du, and M. Thrane, “Problem-oriented and project-based learning (POPBL) as an innovative learning strategy for sustainable development in engineering education,” *Eur. J. Eng. Educ*., vol. 33, no. 3, pp. 283–295, Jun. 2008, doi: 10.1080/03043790802088566.

[5] X. Du, E. d. Graaff, and A. Kolmos, *Research on PBL Practice in Engineering Education*. Rotterdam: Sense Publishers, 2009.

[6] N. C. Brown and C. T. Mueller, “The effect of performance feedback and optimization on the conceptual design process,” in *International Association of Spatial Structures Annual Symposium*, Tokyo, Sep. 2016. [Online]. Available: https://www.researchgate.net/publication/316107726

[7] N. C. Brown, “Design performance and designer preference in an interactive, data-driven conceptual building design scenario,” *Des. Stud*., vol. 68, pp. 1–33, May 2020, doi: 10.1016/j.destud.2020.01.001.

[8] T. Wortmann and B. Tunçer, “Differentiating parametric design: Digital workflows in contemporary architecture and construction,” *Des. Stud*., vol. 52, pp. 173–197, Sep. 2017, doi: 10.1016/j.destud.2017.05.004.

[9] J. Lee, N. Gu, and A. P. Williams, “Parametric design strategies for the generation of creative designs,” *Int. J. Archit. Comp*., vol. 12, no. 3, pp. 263–282, Sep. 2014, doi: 10.1260/1478-0771.12.3.263.

[10] A. M. Masnick, S. S. Valenti, B. D. Cox, and C. J. Osman, “A multidimensional scaling analysis of students’ attitudes about science careers,” *Int. J. Sci. Educ*., vol. 32, no. 5, pp. 653–667, Mar. 2010, doi: 10.1080/09500690902759053.

[11] M. Richardson, C. Abraham, and R. Bond, "Psychological correlates of university students' academic performance: A systematic review and meta-analysis," *Psychol. Bull.*, vol. 138, no. 2, pp. 353–387, 2012.

[12] A. D. Rittmayer and M. E. Beier, "Self-efficacy in STEM," *Applying Research to Practice Resources*, 2008.

[13] Z. Hazari, G. Sonnert, P. M. Sadler, and M.-C. Shanahan, "Connecting high school physics experiences, outcome expectations, physics identity, and physics career choice: A gender study," *J. Res. Sci. Teach*, p. n/a-n/a, 2010, doi: 10.1002/tea.20363.

[14] B. Lawson, How Designers Think, 4th edition. Norfolk, UK: Routledge, 2006. doi: 10.4324/9780080454979.

[15] S. Harter, "Perceived Competence Scale for Children," *Child Dev.,* vol. 53, no. 1, pp. 87–97, 1982.

[16] J. S. Eccles and A. Wigfield, "Motivational Beliefs, Values, and Goals," *Annu. Rev. Psychol.*, vol. 53, no. 1, pp. 109–132, Feb. 2002, doi: 10.1146/annurev.psych.53.100901.135153.

[17] A. Wigfield, "Expectancy-value theory of achievement motivation: A development perspective," *Educ. Psychol.*, vol. 6, no. 1, pp. 49–78, 1994.

[18] D. Pradhan, "Effectiveness of outcome based education (OBE) toward empowering the students performance in an engineering course," *J. Adv. Educ. Phil.*, vol. 5, no. 2, pp. 58–65, Feb. 2021, doi: 10.36348/jaep.2021.v05i02.003.

[19] D. Jonassen, J. Strobel, and C. B. Lee, "Everyday problem solving in engineering: Lessons for engineering educators," *J. Eng. Educ.*, vol. 95, no. 2, pp. 139–151, Apr. 2006, doi: 10.1002/j.2168-9830.2006.tb00885.x.

[20] M. Davis, "Distinguishing architects from engineers: A pilot study in differences Between engineers and other technologists," in *Phil. Eng.*, 2009, pp. 15–30. doi: 10.1007/978-90-481-2804-4_2.

[21] V. B. Arnaud, “Quantifying architects’ and engineers’ use of structural design software,” Master of Engineering, Massachusetts Institute of Technology, Boston, 2013.

[22] J. H. Lee, N. Gu, and M. J. Ostwald, “Creativity and parametric design? Comparing designer’s cognitive approaches with assessed levels of creativity,” *Int. J. Des. Create. Innov.*, vol. 3, no. 2, pp. 78–94, Apr. 2015, doi: 10.1080/21650349.2014.931826.

[23] D. Holzer, R. Hough, and M. Burry, “Parametric design and structural optimisation for early design exploration,” *Int. J. Archit.*, vol. 5, no. 4, pp. 625–643, Dec. 2007, doi: 10.1260/147807707783600780.

[24] M. Tsigkari, A. Chronis, S. C. Joyce, A. Davis, S. Feng, and F. Aish, “Integrated design in the simulation process,” in *Proceedings of the Symposium on Simulation for Architecture & Urban Design*, San Diego, Apr. 2013, pp. 153–162.

[25] R. Feldhausen, J. L. Weese, and N. H. Bean, “Increasing student self-efficacy in computational thinking via STEM outreach programs,” in *Proceedings of the 49th ACM Technical Symposium on Computer Science Education*, New York, NY, USA: ACM, Feb. 2018, pp. 302–307. doi: 10.1145/3159450.3159593.

[26] K. L. Devine, “Using a parametric solid modeler as an instructional tool,” *The Eng. Des. Graph. J.*, vol. 72, no. 2, 2008.

[27] Z. Zhang, Z. Wu, and B. Wang, “Software defined radio-based signal detection and RF parameter estimation platform for enhancing electrical and computer engineering curricula,” in *2016 ASEE Annual Conference & Exposition Proceedings, ASEE Conferences*, *2016*. doi: 10.18260/p.25836.

[28] J. P. Cruz, P. Oliveira, and D. Seabra, “Parameterized exercises in SMC,” Nov. 2016, pp. 5879–5884. doi: 10.21125/iceri.2016.0323.

[29] National Center for Science and Engineering Statistics (NCSES), “Diversity and STEM: Women, minorities, and persons with disabilities,” in *Special Report NSF 23-315*, Alexandria, VA: National Science Foundation, 2023.

[30] T. Roberts et al., “Students’ perceptions of STEM learning after participating in a summer informal learning experience,” *Int. J. STEM Educ.*, vol. 5, no. 1, p. 35, Dec. 2018, doi: 10.1186/s40594-018-0133-4.

[31] S. Kaleva, J. Pursiainen, M. Hakola, J. Rusanen, and H. Muukkonen, “Students’ reasons for STEM choices and the relationship of mathematics choice to university admission,” *Int. J. STEM Educ.*, vol. 6, no. 1, p. 43, Dec. 2019, doi: 10.1186/s40594-019-0196-x.

[32] P. Brown, J. P. Concannon, D. Marz, C. W. Donaldson, and A. Black, “An examination of middle school students’ STEM self-efficacy with relation to interest and perceptions of STEM,” *J. STEM Educ.*, vol. 17, pp. 27–38, 2016.

[33] J. DeWitt and L. Archer, “Who aspires to a science Career? A comparison of survey responses from primary and secondary school students,” *Int. J. Sci. Educ.*, vol. 37, no. 13, pp. 2170–2192, Sep. 2015, doi: 10.1080/09500693.2015.1071899.

[34] A. v. Maltese and R. H. Tai, “Eyeballs in the Fridge: Sources of early interest in science,” *Int. J. Sci. Educ.*, vol. 32, no. 5, pp. 669–685, Mar. 2010, doi: 10.1080/09500690902792385.

[35] A. v. Maltese, C. S. Melki, and H. L. Wiebke, “The nature of experiences responsible for the generation and maintenance of interest in STEM,” *Sci. Educ.*, vol. 98, no. 6, pp. 937–962, Nov. 2014, doi: 10.1002/sce.21132.

[36] P. L. Ackerman, R. Kanfer, and C. Calderwood, “High school advanced placement and student performance in college: STEM majors, non-STEM majors, and gender differences,” *Teachers College Record: The Voice of Scholarship in Education*, vol. 115, no. 10, pp. 1–43, Oct. 2013, doi: 10.1177/016146811311501003.

[37] M. O. San Pedro, J. Ocumpaugh, R. S. Baker, and N. T. Heffernan, “Predicting STEM and non-STEM college major enrollment from middle school interaction with mathematics educational software.,” in *Proceedings of the 7th International Conference on Educational Data Mining*, 2014, pp. 276–279.

[38] P. Vincent-Ruz and C. D. Schunn, "The nature of science identity and its role as the driver of student choices," *Int. J. STEM Educ*., vol. 5, no. 1, p. 48, Dec. 2018, doi: 10.1186/s40594-018-0140-5.

[39] J. Eccles, "Who am I and what am I going to do with my life? Personal and collective identities as motivators of action," *Educ. Psychol*., vol. 44, no. 2, pp. 78–89, May 2009, doi: 10.1080/00461520902832368.

[40] A. Wigfield and J. S. Eccles, "Expectancy: value theory of motivation," *Contemp. Educ. Psychol*., vol. 25, pp. 68–81, 2000.

[41] A. Y. Kim, G. M. Sinatra, and V. Seyranian, "Developing a STEM identity among young women: A social identity perspective," *Rev. Educ. Res*., vol. 88, no. 4, pp. 589–625, Aug. 2018, doi: 10.3102/0034654318779957.

[42] W. Ward Hoffer, "Introduction," in Cultivating STEM identities. Strengthening student and teacher mindsets in math and science, 2016, p. 19.

[43] H. B. Carlone and A. Johnson, "Understanding the science experiences of successful women of color: Science identity as an analytic lens," J. Res. Sci. Teach., vol. 44, no. 8, pp. 1187–1218, Oct. 2007, doi: 10.1002/tea.20237.

[44] R. Dou and H. Cian, "Constructing STEM identity: An expanded structural model for STEM identity research," *J. Res. Sci. Teach*., vol. 59, no. 3, pp. 458–490, Mar. 2022, doi: 10.1002/tea.21734.

[45] S.-C. Fan and K.-C. Yu, "How an integrative STEM curriculum can benefit students in engineering design practices," *Int. J. Technol. Des. Educ*., vol. 27, no. 1, pp. 107–129, Mar. 2017, doi: 10.1007/s10798-015-9328-x.

[46] K. M. Paul, A. v. Maltese, and D. Svetina Valdivia, "Development and validation of the role identity surveys in engineering (RIS-E) and STEM (RIS-STEM) for elementary students," *Int. J. STEM Educ*., vol. 7, no. 1, p. 45, Dec. 2020, doi: 10.1186/s40594-020-00243-2.

[47] N. P. Walsh, “Architecture becomes a STEM subject in the United States,” Arch Daily. 2019.

[48] R. Razzouk and V. Shute, “What Is design thinking and why is it important?,” *Rev. Educ. Res.*, vol. 82, no. 3, pp. 330–348, Sep. 2012, doi: 10.3102/0034654312457429.

[49] Y. Li et al., “Design and design thinking in STEM education,” *J. STEM Educ*. Res., vol. 2, no. 2, pp. 93–104, Dec. 2019, doi: 10.1007/s41979-019-00020-z.

[50] J. Chung, M. A. Cannady, C. Schunn, R. Dorph, and P. Vincent Ruz, “Measures technical brief: competency beliefs in science,” 2016.

[51] Shapediver GmbH, “Shapediver.” Wien, Austria, 2019.

[52] P. Arrendondo, M. L. Miville, C. M. Capodilupo, and T. Vera, *Women and the Challenge of STEM Professions*. Springer, 2022.

[53] D. R. Mullet, T. Kettler, and A. Sabatini, “Gifted students’ conceptions of their high school STEM education,” *J. Educ. of the Gifted*, vol. 41, no. 1, pp. 60–92, Mar. 2018, doi: 10.1177/0162353217745156.

[54] R. S. Nowacek, “Why is being interdisciplinary so very hard to do? Thoughts on the perils and promise of interdisciplinary pedagogy,” College Composition and Communication, vol. 60, no. 3, pp. 493–516, 2009.

[55] M. Borrego and L. K. Newswander, “Characteristics of Successful Cross-disciplinary Engineering Education Collaborations,” *J. Eng. Educ*., vol. 97, no. 2, pp. 123–134, Apr. 2008, doi: 10.1002/j.2168-9830.2008.tb00962.x.

# Chapter 4

## Evaluating Multi-disciplinary Collaboration

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### Abstract

Increasingly, architects and building engineers use parametric modeling programs to explore design solutions as professionals and as students. However, little is known about their combined efficacy and exploration in these tools when working in mixed design teams. While disciplinarily diverse teams of designers have been shown to develop more creative design solutions, this occurs primarily when there is a conducive environment and shared understanding of design goals. Because architects and engineers are traditionally taught to use different tools and processes to address their professional goals, indicators of student combined efficacy in parametric tools are unclear. In response, this research uses a conceptual design experiment to study aspects of design efficacy and exploration behavior of student architect-architect, engineer-engineer, and architect-engineer pairs within a live parametric modeling tool. Dimensions of their collaborative exploration within the tool were recorded, and their success at achieving the desired criteria was rated by professionals. Noticeable performance differences between team types were expected, including that the mixed design teams would better balance all goals and that the homogenous teams would better address their own disciplinary criteria. However, this was not the case when working in a shared, multidisciplinary digital environment as the teams performed similarly despite having different member composition. We discuss several factors, such as the effect of digital design feedback and still developing student design process, that may have a relationship with the design efficacy of the teams when using the study's parametric modeling tool. Future research can further investigate the effect of mutually approachable working environments on design team performance.

Keywords: Collaborative design; parametric design; human-computer interaction; conceptual design; integrated design

## 4.1 Introduction

As the building needs of our society grow in scale and dimension, design objectives for the built environment become more entangled, requiring architects and building engineers to collaborate wholistically on design solutions. Their goals are rarely independent of each other's influence, and major redesigns late in design phases due to incohesive decisions can cost time, money, and the integrity of the design team. When developing comprehensive proposals during the conceptual design phase, computational tools such as parametric modeling can allow designers to rapidly iterate across possibilities and consider qualitative and quantitative objectives. Rather than rebuilding a model for each design variation, parametric models enable designers to easily explore different solutions by changing variables that control objectives in a design problem. However, historically architects and building engineers have followed different design processes to achieve their goals [1], [2]. Yet the exact nature of these differences are not fully agreed upon and may be changing with technology and evolving disciplines [3]–[6]. For example, researchers have proposed that engineers assume problems can be well-defined, start with problem-analysis, and emphasize the "vertical" dimension (linear, procedural) of systems engineering, while architects assume partially defined problems and approach them with an opportunistic, argumentative process that emphasizes the horizontal dimension (iterative, problem-solving) [1]. Yet there is diversity among engineering disciplines in their exact approach, and there has been more recent emphasis on iterative problem-solving for engineering problems, potentially breaking this dichotomy [7], [8].

Despite this ambiguity, many researchers still observe differences specific to architects and building engineers [6], [9]–[11], and different approaches may hinder their combined efficacy when working in parametric tools. Stemming from their disciplinary training as students, they may even approach design differently based on the professional identity of their collaborators [12]. Research has shown that diversity in teams can lead to more creative solutions, but an inconducive design environment and lack of shared understanding can impede design performance [13]. At the same time, designers increasingly use digital forms of communication to collaborate, such as video meetings with screensharing for quicker feedback about design performance. When working in remote, parametric environments, it is unclear how students' disciplinary identity may predict their design efficacy and behavior when collaborating with designers of similar or different educational backgrounds.

### 4.1.1 Parametric Models as Design Tools

Parametric 3D-modeling tools allow designers to readily explore design options by adjusting model variables and reviewing geometric and performance feedback, which can enable quick, multi-disciplinary decision-making. These tools can potentially improve on traditionally separate design and analysis software, which may not most optimally address the range of complex requirements [14]. For example, architects rely heavily on sketching [15] and digital geometry tools [16] while building engineers use discipline-specific analysis programs such as

SAP2000 and ETABs for structural design or EnergyPlus for energy modeling. While previous research has shown 3D digital modeling to be a less conducive environment for collaboration compared to sketching [17], this was due to the tedious nature of digital model building and may not apply to all forms of digital design exploration. An advantage to computational tools is that they enable efficient design responses and allow for more avenues of communication between the professions [18].

Specifically useful for early design collaboration, parametric 3D modeling tools allow designers to quickly explore a range of qualitative design options and receive multi-dimensional feedback about quantitative design performance [19], [20]. Such an environment allows rapid exploration, albeit with more constraints, but also provides more information about the design than a sketch. These tools can improve design performance [21], and previous research has supported that working in parametric models is a viable environment for design decision-making [22]–[27]. Parametric design tools can be part of an equally accessible environment for different professions that provides quick, simultaneous feedback about both geometry and performance [28]–[30]. Building designers increasingly use parametric design thinking to explore solutions in a variety of applications, such as building forms [31], structural design [28], building energy [29], and urban development [32]. Some established examples of parametric modelling in practice include the Beyond Bending pavilion at the 2016 Venice Biennale [33] and the iterative structural, energy, or daylighting analyses used by firms like ARUP [34] and Foster + Partners [35].

In addition, computational design tools can be combined with digital platforms for collaboration. Due to shifts in the nature of work, expedited by the pandemic in 2020, online video meetings are increasingly used by the AEC community to design real buildings [36] and can be beneficial to conceptual design development [37]. As remote work becomes more normalized, digital mediums are increasingly used as the context for real design conversations in both engineering and architecture [36], [38]. As an alternative to screen sharing and sketching in remote meeting platforms, shared online parametric models and their corresponding visualizations can provide an additional form of feedback. While dynamics within design teams in digital technologies have been studied before [39]–[41], much of the work does not account for the context of parametric design environments, nor do they directly connect team efficacy based on team composition and defined design criteria. Understanding disciplinary identity when using these tools may influence how designers approach collaboration in computational platforms, resulting in differences of combined team design efficacy.

### 4.1.2 Collaborative Design Processes of Architect-Engineer Teams

Collaboration between diverse teams has been studied, characterized, and documented [13], [42]–[45], but there is still much to understand about the specific interactions of engineers and architects, particularly when attempting to evaluate indicators of design efficacy. To best include efforts of both architects and engineers, whose performance could be measured by different metrics, we follow Marriam-Webster dictionary's definition of efficacy to be "the power to produce an effect." Specific to buildings, design efficacy can be used to describe successful achievement of desired outcomes such as cost, sustainability, efficiency, and discipline-specific goals like spatial needs and structural requirements. Previously, engineering efficacy has been measured by how thoroughly engineers are able to address specified criteria [46] and by measurable, outcome-based metrics [47], [48]. Conversely, efficacy in architecture is harder to identify as architectural goals can be more qualitative or experiential. Methods such as the Consensual Assessment Technique (CAT) method [49] have been used to evaluate design quality when criteria are subjective and less measurable, such as in graphic design [50].

Also significant is that building designers rarely work alone and must consider both qualitative and quantitative goals, which can obscure representations of their design process. While diversity in design teams stimulates creativity, with heterogeneous teams benefitting from a combination of expert perspectives, improved team performance most readily occurs if there is shared vocabulary and a conducive design environment [13]. The team should also share similar conceptual cognitive structures [51], which may differ by profession. While diverse teams of engineers and architects work towards the same end goal of a building, some acknowledge their different design processes and have shown they use separate design tools [52]. However, as argued earlier as it is a main motivator of this paper, the development of new design models and the context of digital tools makes the distinctions of their processes are less clear.

No model of design process has perfectly captured the activities of a whole profession [3] and the integration of digital tools have further confounded understanding of design process. Oxman [4] recognized that while some concepts reoccur in digital tools, design methods can vary depending on the media used. Design process models in parametric tools of architects have been illustrated by Stals et. al. [26] as the amplified exploration of ideas compared to processes supported by traditional tools. Oxman [27] considered parametric design as a shift in understanding of design thinking, less bound by a representative model. However, these studies on parametric tools did not consider the differences between architects' and engineers' exploration. Increasingly, architects and engineers work in these tools together, therefore studying the collaborative efforts is valuable to better understand and eventually incentivize effective teamwork, given potential disciplinary barriers. Such challenges in design collaboration may stem from designers' education where they begin to identify with a profession [53]. Understanding the behaviors of student populations when using these tools can inform how they may collaborate in parametric environments in their future careers.

### 4.1.3 Decision Processes of Student Designers

While many assert that architects and engineers follow different design processes, there is evidence to support that student designers may not yet possess the cognitive processes that are emblematic to their profession. Kavakli and Gero [54] found that when comparing series of cognitive actions in design, students followed a greater range of sequences of cognitive processes compared to experts, who employed a smaller range of sequence variation and were more efficient in their cognitive actions. Similarly, Ahmed et al. [55] found that students tend to follow "trial and error" processes and do not have as refined design strategies as professionals, who were more systematic. However, these studies do not account for the influence of computational decision-making on design. Abdelmohsen and Do [56] found that novice architect designers performed prolonged processes to achieve the same goal as experts when responding to both sketching and parametric modeling tasks. In their study, though, students worked independently and did not account for team collaboration in parametric tools.

As students are still developing as design thinkers in their fields, it is important to consider how they may collaborate with teammates who are trained in a different discipline. Architecture and engineering students often receive divergent instruction on how to address design goals when working in digital tools. While engineers have traditionally followed problem-solving methods with an emphasis on "right" answers [57], this has been challenged recently as instructors incorporate more project-based learning [58]. There is also increased discussion of preparing engineers for cross-disciplinary design thinking [59]–[61]. Conversely, architectural education emphasizes spatial thinking with 3D modeling and incorporates digital forms of learning though emerging tools [15], parametric models [62], optioneering [63], and collaborative methods [64]. While distinctions in design education may become harder to define as both disciplines evolve, many still note disciplinary divides between architecture and engineering education and practice [11]. Both types of expertise also tend to play defined roles in practice. In traditional building design procedures, architects may finalize many characteristics of a building before consulting with their engineers, limiting the autonomy of engineers to positively influence the design. Researchers from both professions suggest that early integration of engineers in the building design process can improve design performance and efficiency [65], [66], but early integration has its challenges as the professions have developed different disciplinary cultures [67]. Overcoming these issues can be considered in their education as multi-disciplinary thinkers, but we need to first understand how they behave in mixed teams working in a parametric modeling environment.

#### 4.1.4 Research Questions and Hypotheses

In response, this research asks two questions about student architect and engineer designers: (1) **How does team composition relate to design efficacy in a shared, live parametric design environment?** And (2) **How does team composition relate to design exploration in this environment?** To answer these questions, a study was developed that compared pairs of two architecture students (A+A), two engineering students (E+E), and one of each discipline (A+E) as they jointly responded digitally to a conceptual design task with two engineering and two architectural criteria. Thirty pairs of designers, with ten of each team type, worked in an equally accessible online parametric design space which allowed them to explore a pre-built model using editable sliders. The model provided considerable geometric diversity and real-time engineering feedback, addressing simulated performance needs of both professions and reducing barriers in aptitude of disciplinary tool familiarity. The teams' ability to address the four criteria, as assessed by professional evaluators, was used to measure the efficacy of the final designs. Audio, video, and tool-use recordings of the design sessions captured information about the teams' collaborative efforts and design exploration.

It was hypothesized that the diverse teams (A+E) would be more effective at addressing all the design criteria and that design strategies would vary by team type. This hypothesis was based on previous literature describing the environment-dependent benefits of diverse teams. However, we noted the potential of no significant differences between team performance, possibly indicating unexpected and equalizing influences of the parametric tool on design processes. We also considered that disciplinary differences might not yet emerge in mutually approachable environments for student designers who are not yet experts in their field. Additionally, as this study was conducted through a digital video interface, it speaks to the potential screensharing strategies present in remote, collaborative working environments. Understanding how student architects and engineers cooperate in digital, parametric platforms can discern effective team strategies in emerging design environments, inform educators about the preparedness of future designers to think multi-objectively, and reveal unexpected influences of parametric tools on conceptual design processes.

## 4.2 Materials and Methods

To understand how diverse pairs of student engineers and architects perform compared to same-wise pairs, this research relied on two digital design tools that are increasingly used in practice: a readily approachable parametric modeling platform, and remote video meetings to host collaborative design sessions. While parametric design can occur at various stages of building development and be applied to many scales of design detail, this work focused on the conceptual design phase of a stadium roof, which required both architectural and engineering input and was an approachable task for student designers. Although naturally occurring design processes can manifest in many environments, this work focused on parametric models as design tools to capture evidence of effective behavior specifically in this medium.

The teams worked remotely in an online parametric tool, not native to either discipline, which provided visual and numeric feedback. The intent was to facilitate an environment that was not directly familiar and thus did not favor the efforts of either profession. Participants performed the design task together in an online video meeting, which was able to record information about their exploration. In addition, the teams submitted screenshots of their final design and a design statement, which four professional designers used to evaluate team efficacy in addressing the design task objectives. Figure 4-1 illustrates the study's protocol with an example of the design tool interface.

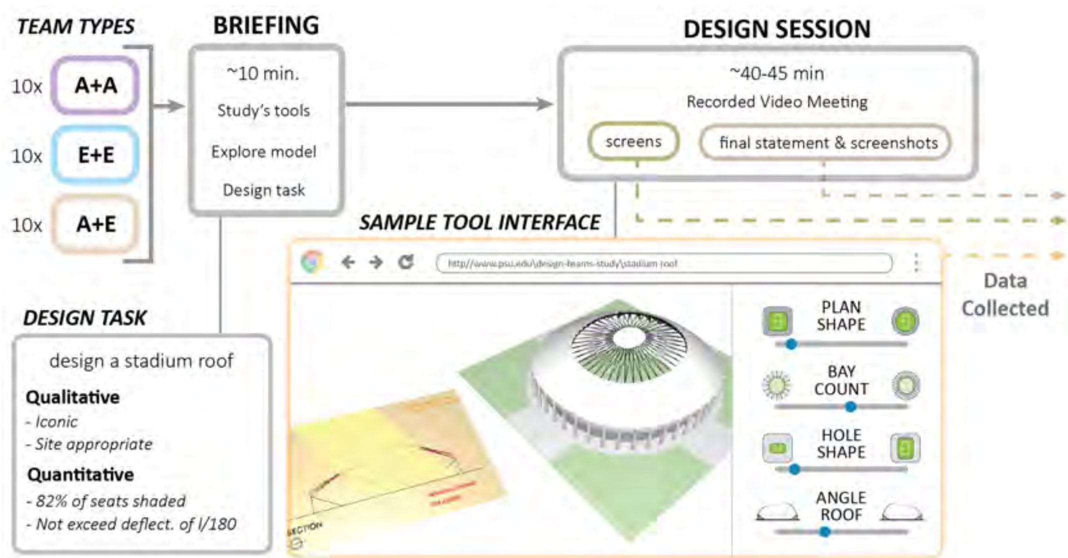


Figure **4-1**. Methodology. Overview of the methodology, design task, tools, and data. collected from the study. The sample tool interface shows 4 of 10 parameters controlling the model and a sample of the 3D modeling space with visual geometric and performance feedback.

### 4.2.1 Design Session Procedure and Participants

The study was conducted through recorded online video meetings and the sessions lasted approximately one hour. In the first 20 minutes, the teams were briefed on the study tools, given the design task, and allowed 5 minutes to become familiar with the materials before developing a design with their assigned partner. The teams were then allowed 30-35 minutes to work on their design and submit deliverables from the design task.

Prior to running the study and collecting data, the interface and protocol were piloted on 3 teams to verify the clarity of the design task, usability of the tool, and accuracy of the data collection methods. The sample participants were either members of the research team who did not participate in the script development or graduate students in an architectural engineering program with at least 1 year of experience in 3D parametric modeling. The sample participants were able to finish the task in the allotted time. Upon completing the test design session, these sample participants provided feedback about the study's procedures, which were then further refined. The sample data was used to ensure the reliability of the data collection, processing, and analysis approaches.

This study was approved by the researchers' Institutional Review Board. Participants were structures-focused engineering or architecture students from one of two large, public U.S. Universities. Participation was limited to 4th or 5th year undergraduates with AEC internship experience for engineers and National Architecture Accrediting Board (NAAB) accredited structures courses for architects, or students of either discipline at the graduate level. Participants were paired based on disciplinary major and availability. The research questions of the study were not revealed to the participants so to not influence their performance. While the moderator was available to answer questions, they had minimal interaction with the teams during design and did not prompt any behaviors.

Although the students may experience more elaborate design challenges over longer periods of time through their coursework or in their future professional practice, replicating extensive, multi-year design processes is beyond the scope of this paper's research questions. It has been established that design study protocols must consider limitations of tools and resources to collect clear, dependable data [68]. To reduce cognitive fatigue and minimize uncontrollable external influences on team behavior, this research used a concise design task and focused metrics to evaluate the team processes.

### 4.2.2 Design Task Criteria

The conceptual design task asked participants to develop the geometry of an Olympic stadium roof for a fictional site plan in a tropical climate. There is precedent for stadium roof design as a good sample project to judge designer performance in parametric modeling [34]. The design statement provided to the designers contained four criteria used as design goals and to assess the efficacy of the teams. Two of the criteria were qualitative requirements that aligned with architectural values: that the design be iconic and site appropriate. The other two quantitative requirements aligned with engineering goals: that the roof shade a certain percentage of seats during noon on the summer solstice and not exceed a maximum deflection limit, which the participants were required to calculate. These goals were considered accessible based on participants' level of study and degree requirements. For final deliverables of their proposed conceptual design, teams were asked to submit 3-6 screenshots and a 5-8 sentence design statement that discussed how their design addressed the prompt. Additional detail of the design task and requirements can be found in Appendix C.

### 4.2.3 Design Environment Details

The study's primary tool consisted of an online parametric stadium roof model that the designers could edit by changing ten variable sliders. The tool was intended to be neutral to not favor the capabilities of one profession over the other, and novel to the designers, in that no participant had used the exact interface before. While the parametric model would limit the detailed development of the project, this design task asks the participants to focus on developing the roof design in the late-conceptual design phase, when aspects like the structural systems and likely materials would have already been decided.

The model was constructed in the parametric modeling program Grasshopper and uploaded to Shapediver [69], an online file hosting platform that allows external users to change model variables and obtain design feedback without editing the base file. Shapediver and similar cloud-based platforms have been gaining popularity in several fields due to their ease of access from a browser and utility in developing 3D model solutions. The Shapediver API interface was used to embed the model in a custom website, built for the study, that tracked user click and design data, such as when variables were changed. Before designing, participants were shown how to use the tool and they independently accessed the website during the video meeting. They were briefed on how to share their screens, but screen sharing was not required nor explicitly encouraged. Figure 4-2 shows the structure of the tool's files and examples of three screensharing strategies that may be used by the design teams, such as one person sharing their screen and the other watching for the whole session, one person sharing their screen while the other person keeps working or sharing screens back and forth throughout the session.

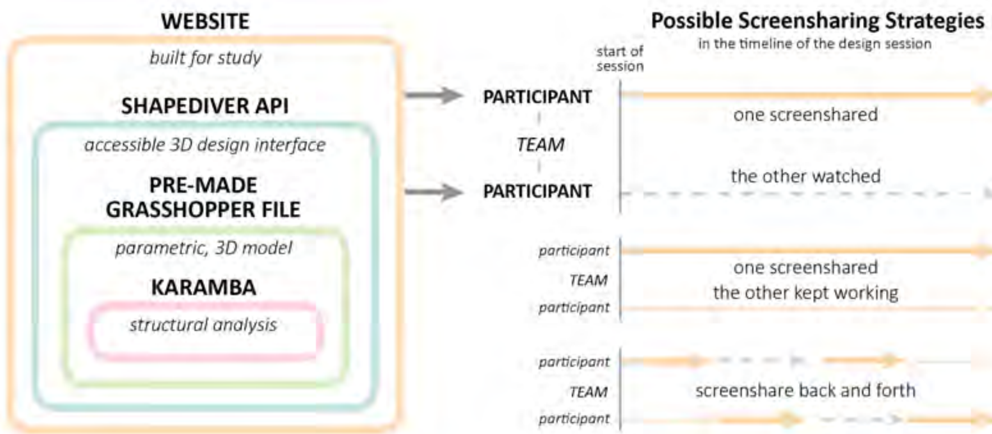


Figure **4-2**. The design tool's structure and possible screensharing strategies used by participants to collaborate in the tool.

The tool's ten editable sliders mostly modified geometric qualities of the stadium and the variables all impacted the four design criteria in some capacity. Authentic to a design challenge in practice, the base model was built such that no "best" solution existed. For example, a larger roof area improved shading, but also increased deflection, which was undesirable. In the model, the quantitative criteria were achievable for a range of visual solutions but could not be met under all variable settings. Providing ten variables allowed designers of both types to consider combinations of solutions and use different approaches to explore the design space. The variables were mostly continuous, which gave participants the ability to directly manipulate the design. Collectively across all variables, there were over 5 trillion possible solutions. While the parametric model would limit the detailed development of the project, this design task asks the participants to focus on developing the roof design in the late-conceptual design phase, when some aspects such as the structural systems and likely materials would have already been decided. In addition, the tool used Karamba3D [70] to perform live deflection calculations of the roof as the users changed the variables. Details about the tool's variables and internal calculations of deflection and seat shading can be found in Appendix D.

### 4.2.4 Methods for Evaluating Team Efficacy and Exploration

To answer the study's research questions, three streams of data were evaluated: final design efficacy based on professionals' evaluations, exploration behavior based on engagement with the tool, and team collaboration strategies based on how they chose to work remotely in the video meeting.

#### *4.2.4.1 Assessing Team Efficacy*

Following the design task, team efficacy was assessed by four professionals (one licensed engineer, one engineering professor, one licensed architect, and one architecture professor) for how well the teams addressed the criteria in their visual submissions and design statements, based on the requirements of the design task. All reviewers held professional degrees in their field and were located at schools or firms in the southwestern US, northeastern US, or western Europe. The licensed professionals had at least 8 years of experience in practice and the professors taught for at least 7 years. Their evaluation followed the Consensual Assessment Technique method [49], which uses professionals to evaluate design quality, responding to questions about criteria performance using a Likert scale. The questionnaire and additional details for their evaluation procedures are provided in Appendix E. The CAT method is often used in evaluating design ideas that rely on qualitative evaluation, but it has been used in engineering applications as well [71]. The professional evaluators were asked "how well did the project from team X address criterion Y of the design task." They reported their opinions on a five-item scale including the responses "not at all," "somewhat well," "moderately well," very well," or "extremely well." The professionals completed their assessments individually and were not told which team type they were evaluating. To mitigate evaluation fatigue, each professional evaluated only 12 designs (four of each team type). To verify the agreeance between the evaluators, they evaluated six of the same projects and six different projects. For the same six projects that they evaluated, an Intraclass Correlation Coefficient was calculated for all criteria.

#### *4.2.4.2 Assessing Team Collaborative Design Exploration*

In addition to efficacy, design exploration was documented by measuring the teams' interaction with the design tool using click data and by observing how the teams collaborated in the shared work environment. As the professions increasingly rely on online forms of design cooperation, considering the student participants' behavior when working in the digital environment can inform how the professions use these tools when designing.

To capture the designers' exploration of the tool, we included a tracking mechanism in the design website that recorded variable changes and corresponding iterations during the session. Comparing differences in number of variables explored and iterations tested can suggest the relative breadth of the design exploration. Yu [25] observed that parametric design has two kinds of cognitive processes: "design knowledge," which relies on a designer's knowledge for their decisions, and "rule algorithm," in which the designer's decisions respond to the rules of the model. Using more variables and creating more iterations can reflect the application of both cognitive processes. Although the teams in our study did not exhaustively engage all the variables, they mostly adjusted all variables at least once. In the time allowance of the study, this reflected enough dimensions for authentic engagement, but not too many variables for the designers to consider. The numbers of iterations were compared to the efficacy ratings for each criterion, since more iteration may relate to improved design performance. Significant iteration, though, might align with an architect's process, whereas an engineering process may lead more directly to a solution.

#### *4.2.4.3 Assessing Team Screensharing*

The method by which the teams chose to collaborate in their visual efforts was also noted. Although previous research has considered collaboration through digital file exchange [72], it did not account for active environment engagement. Alternatively, virtual reality tools can allow two users to move around in the same environment with an integrated video platform, but virtual reality is not yet pervasive in architecture and engineering firms for collaborative design environments. In the online environment used in this study, participants were allowed to choose how to work in the digital modeling environment. They could develop their solutions through various screen-sharing tactics, which were observed by team type. The researchers noted which partner shared screens, how long they shared, and if they alternated screensharing. This empirical approach to describing team collaboration styles allowed the researchers to note new behaviors as they occurred. If the majority of a team type's pairs followed the same screensharing method to develop their models, it may speak to a likeness in collaborative process, but if all the pairs behave differently, this would further confound the disciplinary process identities when working in video shared, parametric design environments.

## 4.3 Results

A total of 30 designs were created, with 10 designs from each team type. Figure 4-3 shows screenshots of 18 of the 30 projects. Initial visual assessment suggests a range of solutions with the most visually noticeable characteristics being plan shape, roof angle, and roof coverage. However, the professionals' assessments provide more critical examination of the teams' efficacy, which provided a baseline by which to compare the teams' collaboration and design space exploration.

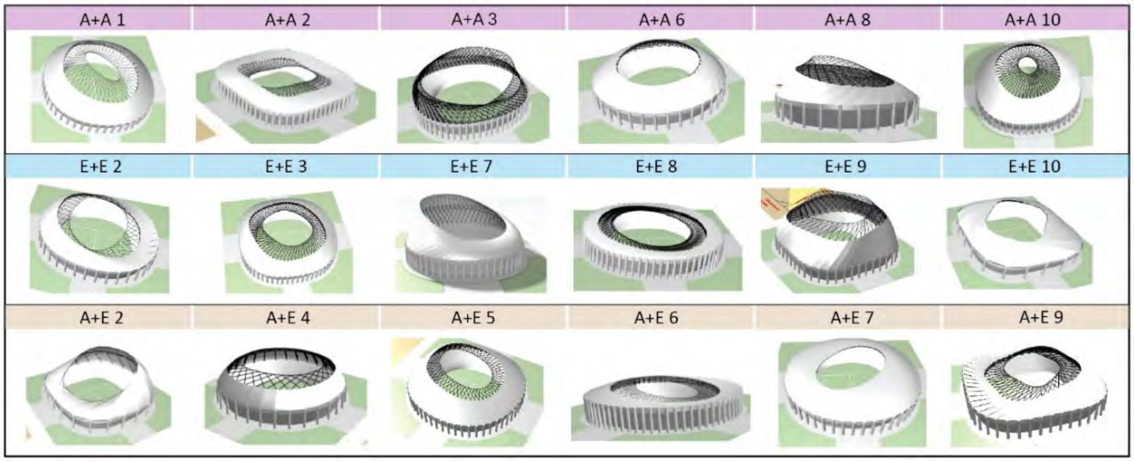


Figure **4-3**. A sample of eighteen of the thirty final designs with six from each team type.

### 4.3.1 Professional Assessment of Team Efficacy

To determine team efficacy, four professionals evaluated the projects for how well the design pairs addressed the four criteria. Figure 4-4 shows the professional's evaluations as box and whisker plots of the team type efficacy for each objective. The A+A teams had higher average effectiveness than the other teams at meeting all four criteria, but in "site" and "deflection," at least one of the A+A teams was judged to have not addressed the criteria at all. The A+E teams had the lowest average effectiveness in "iconic," "shading," and "deflection," with the largest range in performance. While the E+E teams were not more effective than the other team types at any criteria, all E+E teams were at least somewhat effective at addressing the four criteria.

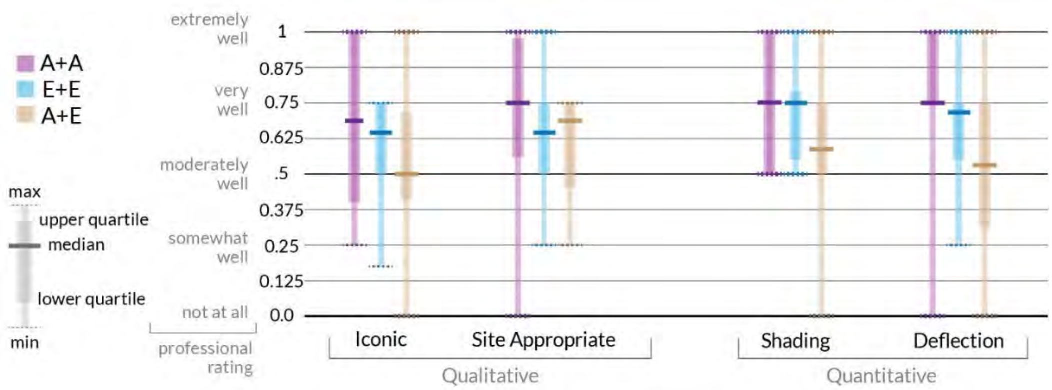


Figure **4-4**. The professional assessment of efficacy for each team type of each criterion.

A Kruskal-Wallis test was performed for each criterion to determine if there were any statistical differences between team types at a p=0.05 level of significance. No team type was significantly different in efficacy of achieving any of the four criteria, with deflection having the lowest p-value of 0.334. Since five of the twelve team type criteria had evaluations scoring from 0 to 1, the outlying values in the large range may have overly influenced the data, reducing the data's statistical significance. To test if the large ranges had a negative impact on statistical significance, the highest and lowest evaluation value for each team type in each criterion were removed, and the Kruskal-Wallis tests were run again. While the p-values for each criterion in the Kruskal-Wallis test were closer to a significance level of 0.05, they were still not significant. The p-values from these tests are shown in Table 4-1.

Table **4-1**. The p-values of Kruskal-Wallis tests for significantly different results in team type efficacy.

| Criteria | All Projects | Remove max. and min. |
|---|---|---|
| Iconic | 0.535 | 0.461 |
| Site Appropriate | 0.439 | 0.357 |
| Shading | 0.495 | 0.462 |
| Deflection | 0.334 | 0.136 |

Based on their ratings, an Intraclass Correlation Coefficient was calculated across all the evaluators for all criteria. It was found to be 0.719, which meets an acceptable level of agreeability. While coefficients between 0.900 and 1.000 are considered in very high agreeance, and above 0.7 are considered acceptably high, interpretation of coefficients are conditional to each application. In this study, because the assessments are both qualitative and quantitative, judged by four raters with unique expertise, and use an evaluation scale with five options, an agreeance of greater than 90% would be unexpected. The CAT method for creativity evaluation, which often uses ICC to consider evaluator agreeance, assumes that the professionals all have the same area of expertise. In contrast, this study uses both architects and engineers to evaluate the projects, who have their own areas of expertise, and still meets a level of agreeance above 0.7 with an ICC of 0.719.

### 4.3.2 Characteristics in Collaborative Exploration

The teams' exploration of the design space was measured by their engagement with the design tool and by their behavior when collaborating in the online environment.

#### *4.3.2.1 Characteristics in Collaborative Exploration*

Figure 4-5 shows the number of iterations and average variables changed for each team type. No team type explored a statistically greater number of iterations than the other team types nor changed a greater number of variables, based on a Kruskal-Wallis test at $p=0.05$ level of significance. However, comparing iterations to individual criteria may yield more informative results.

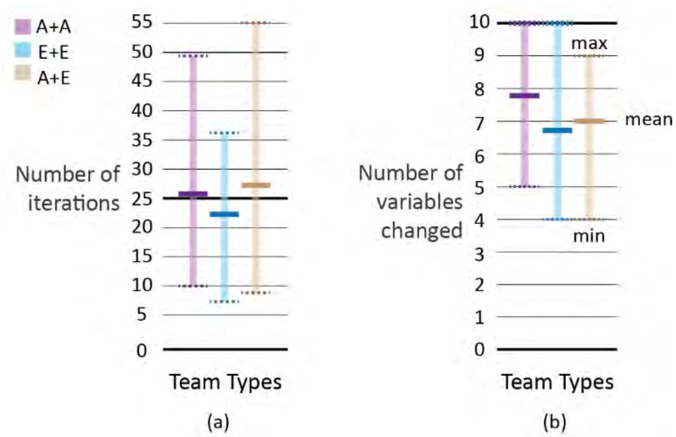


Figure **4-5**. Design exploration of teams by (a) the number of iterations explored by each team type and (b) the number of variables changed by each team type.

When considering the relationship between the number of iterations created by each team type to the efficacy performance ratings for each criterion, a pattern emerges. Figure 4-6 shows the plots of Criteria Ratings vs. Iterations for each criterion and their fitted linear regression line. The figure also provides the slope for each linear regression equation and the p-value at a 0.05 level of significance based on a simple linear regression analysis for statistical significance between the variables. For the test, the null hypothesis is that the slope is 0 and the alternative hypothesis is that the slope is not 0. The p-values of the regression analyses are greater than 0.05, therefore there is not enough evidence to say that iterations have a linear statistical relationship to criteria efficacy. However, the signs of the slopes for their relationship are consistent in each criterion. While more iterations relate positively to greater criteria efficacy for the E+E and A+E teams, the opposite is true for the A+A teams, for which the relationship is negative or negligible.

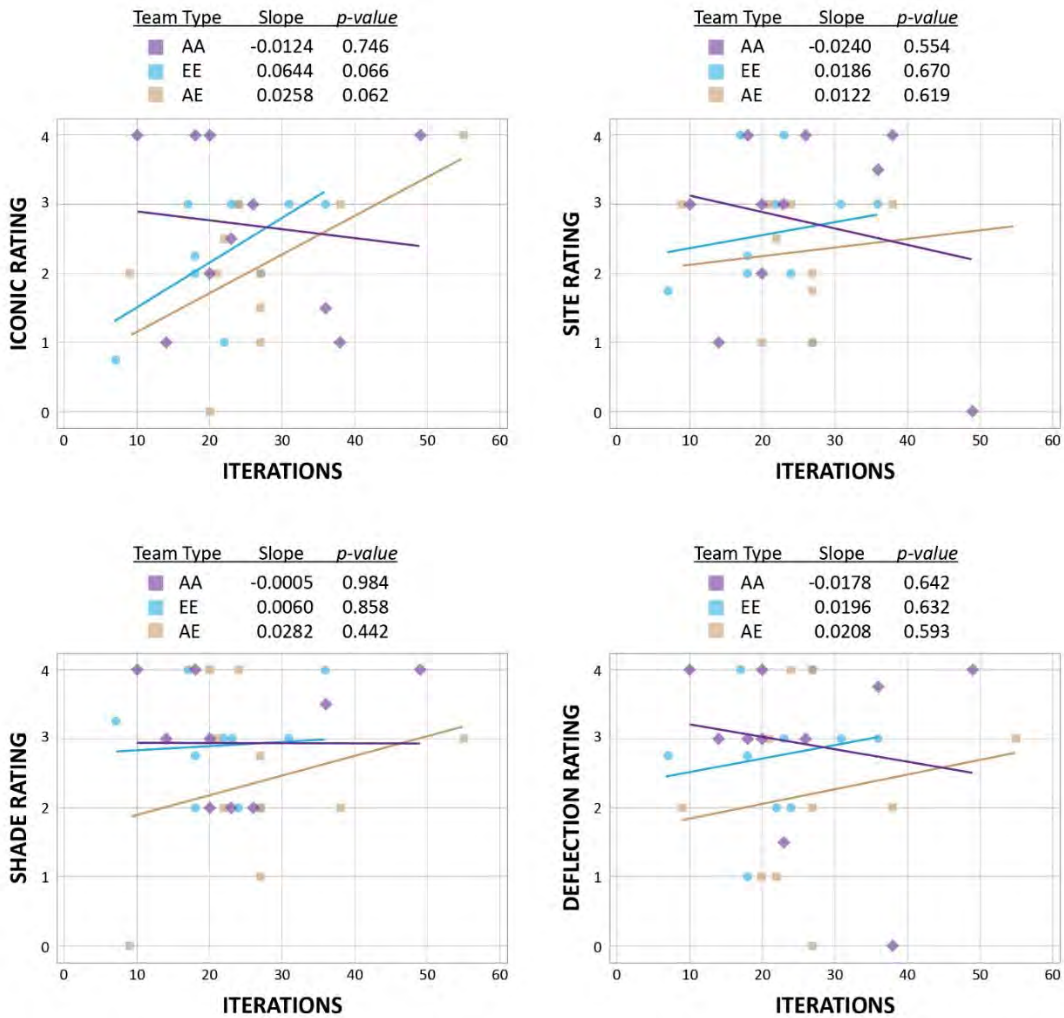


Figure **4-6**. Plots of criteria efficacy rating vs iterations by each team, showing the fitted linear regression line for each team type and stating the slope of the simple regression analysis equation and its associated p-value.

#### *4.3.2.2 Screen Sharing the Collaborative Environment*

When working collaboratively in the design environment, we noted several patterns on how pairs explored the model while using the remote design tools. Figure 4-7 shows a sample of the different screensharing strategies and the number of teams for each team type that followed the strategies. The most common method for sharing ideas, labeled Strategy 1, was when one team member shared their screen within 5 minutes of starting their session and moved in the model while the other designer watched and made suggestions. This strategy was followed by 5 A+A teams, 7 E+E teams, and 4 A+E teams. Strategy 2 was when one person shared, but their partner continued working in their own model. Strategy 3 was when each teammate shared their screen at least once. In some cases, teams shared their screen multiple times. Strategy 4 represents other methods. For example, team AE10 never screenshared, but verbally updated each other about their variable settings when they found solutions that they liked. Team AA8 worked independently and only shared their design towards the end of the session. A third team, AE4, chose to screenshare both designers' screens while allowing both designers to control the mouse. There was no screensharing method consistently used by a team type.


**Screensharing Strategies by each Team Type**

| Team Type | Strategy 1 | Strategy 2 | Strategy 3 | Strategy 4 |
|---|---|---|---|---|
| AA | 5 | 2 | 2 | 1 |
| EE | 7 | 1 | 2 | 0 |
| AE | 4 | 0 | 3 | 3 |

Figure **4-7**. The strategies used by the team types when screensharing, showing 13 of the teams' strategies.

## 4.4 Discussion

In summary, we hypothesized that when working in a parametric, digital modelling environment, diverse teams would show significantly better performance when A+E, A+A, and E+E pairs were given the same design task, but this finding was not supported by the data. It was also expected that explicit behaviors based on team type would become evident in efficacy or design space exploration. However, this was not the case. It was surprising that the teams performed similarly and did not show greater proficiency at addressing their own disciplinary design criteria. While some differences between team types were noted, few rose to the level of statistical significance at traditional confidence levels. Further discussion for each research question is given below:

RQ 1: **How does team composition relate to design efficacy in a shared, live parametric design environment?** Diverse pairs of building designers were not significantly more effective at addressing the design criteria than same-wise pairs, despite what is predicted by existing literature. Although the provided parametric design environment may not have allowed for enough design diversity between team types, it is possible that for the student designers, live feedback from the parametric tool may have benefitted the efforts of the teams in absence of other discipline. In a traditional practice workflow, the professions serve their own roles and provide disciplinary expertise, and there is a lag in communication while they perform their respective responsibilities in sequence. The shared modeling space with multidisciplinary feedback may have partially performed jobs of both architects and engineers at the resolution of early-stage design. However, it is also possible that student designers are not yet proficient in their field and did not perform in a way that is emblematic to their profession and therefore did not show differences in performance. In addition, Lee et al. [51] reports that, regarding creativity, simply including designers with different backgrounds does not guarantee improved results if the designers do not share mental models for problem solving. Future research should consider whether providing live, visual, quantitative feedback, alongside geometric flexibility, can help serve roles of both professions and increase the ability of homogeneous pairs to manage multidisciplinary criteria.

RQ 2: **How does team composition relate to design exploration in this environment?** Although no team type explored the model significantly more based on number of iterations and number of variables changed, the increase of iterations compared to team type efficacy does suggest some differences between groups. While greater iterations related to improved design efficacy ratings for the E+E and A+E teams, the same was not true for A+A teams. Since iterative processes are associated with architects [42], an increase in iterations should have, theoretically, improved the design performance by all teams, especially the A+A teams. Also, no team type consistently followed the same strategy for sharing screens to develop their designs. Screensharing in collaboration is not specific to a particular profession and may not differ by disciplinary background, but it is important in effective student education [73], [74]. The students in this study may be better at working remotely through screensharing due to their remote experiences in the Covid-19 pandemic. In addition, the relationship of team type characteristics to team efficacy is inconclusive, suggesting that diversity in engineering and architect teams does not guarantee improved results when considered in the context of a collaborative, parametric environment.

A summary of what was learned regarding each research question is provided in Figure 4-8. Overall, the study's metrics may suggest the presence of an equalizing influence of parametric tools on efficacy and exploration or that student designers do not have differing behavior between professions in the provided design environment. Parametric tools have been shown to positively support design performance [75], and it could be that the mutually approachable environment influenced the design process. However, impacts on design team performance can be generally hard to discern, as previous research on construction design teams have also shown inconclusive results [76]. Although further research is needed to understand the impact of multi-disciplinary tools on mixed disciplinary teams, the lack of distinct differences presented in this paper provides a baseline for assessing exploration and efficacy in the context of collaborative design.

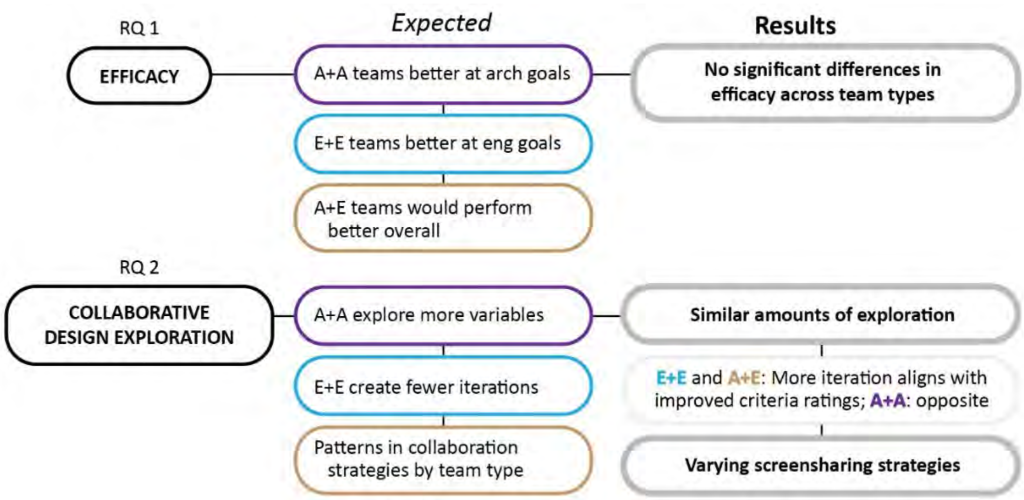


Figure **4-8**. Summary of the findings from the study, focusing on the team efficacy and how efficacy related to collaboration and design exploration.

### 4.4.1 Limitations

There are several limitations to the study. Despite its methodological advantages, using a pre-made parametric design space does not allow for exhaustive analysis of all possible conceptual design approaches for buildings. However, as McGrath [68] established, there are three goals in understanding and quantifying team group interaction: generalizing of evidence from a large population, precision of measurements, and realism of the simulation. This study conducted concise yet somewhat abstract design simulations to achieve precision of measurement across a reasonably large population, which sacrificed some aspects of realism of the design simulation. However, having fewer participants with rich data is reasonable for studying design to capture the subtlety and depth of the process, particularly in studies which follow protocol analysis methods [77] (p. 15).

McGrath also acknowledges that to evaluate the results of a team groups study, one should be critical of the methods and tools used that are specific to the study or profession. While this study uses one design challenge, in focusing on just the stadium roof, the designers were able to complete the task in the allotted time and respond to the disciplinary specific design goals using their respective knowledge. Other limitations could include perceived ambiguity in the design criteria, or the fact that the data collected for collaboration and exploration does not perfectly characterize those corresponding behaviors—there is some subjectivity in mapping between data collection and behavior for a specific design challenge. Nevertheless, the study relied on established methods for design evaluation and had clear protocols for data collection to determine statistical significance in the design teams' different characteristics.

## 4.5 Conclusions

This paper presented the results of a design study that considered relationships between efficacy and behavior of diverse and same-wise pairs of student engineer and architect designers. While it was expected that diverse teams would be more effective at addressing varied design criteria, a professional assessment of the designs did not suggest that any team type performed significantly better than the others. However, the lack of significant differences in design performance and behavior raises questions about the influence of the digital design environment on the design process—it is possible that an online digital modeling platform may have influenced design strategies to converge. Subtle differences between the A+A and E+E teams' behavior suggest narratives relating to team type characteristics, but there are few notable distinctions. In applying these results to practice, it may be that parametric modeling tools can be helpful for designers of either architecture or engineering backgrounds to explore design spaces. Such approaches may not be useful for all professional firms or all design stages, but managers may consider opportunities afforded with parametric models especially during conceptual design and other instances in which options are visually compared by multidisciplinary teams. Future work will consider how teams of professional engineers and architects may collaborate when working on the same design task in a more extensive design scenario. This will overcome limitations introduced by the reliance on the parametric design space. In addition, the methods used in this study could be applied to understanding the behaviors of larger building design teams over more extensive design sessions. As design tools evolve and design requirements continue to push construction boundaries, it is important to continually understand effective indicators of architect-engineer team performance.

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**References**

[1] N. Cross and N. Roozenburg, "Modelling the design process in engineering and in architecture," *J. Eng. Des.*, vol. 3, no. 4, pp. 325–337, Jan. 1992, doi: 10.1080/09544829208914765.

[2] W. Visser, "More or less following a plan during design: opportunistic deviations in specification," *Int. J. Man-Machine Stud.*, vol. 33, pp. 247–278, 1990, doi: 10.1016/S0020-7373(05)80119-1.

[3] K. Gericke and L. Blessing, “Comparisons of Design Methodologies and process Models Across Disciplines: A Literature Review,” in *International Conference on Engineering Design*, Denmark, 2011.

[4] R. Oxman, “Theory and design in the first digital age,” *Des. Stud.*, vol. 27, no. 3, pp. 229–265, May 2006, doi: 10.1016/j.destud.2005.11.002.

[5] D. Wynn and J. Clarkson, “Chapter 1: Models of Designing,” in *Design Process Improvement: A review of current practice*, J. Clarkson and C. Eckert, Eds., 2005, pp. 34–59.

[6] N. Cross, *Design Thinking: Understanding how Designers Think and Work*. Oxford: Berg, 2011.

[7] J. Clarkson and C. Eckert, *Design Process Improvement: a review of current practice*. Springer, 2005.

[8] N. Cross, *Engineering Design Methods: Strategies for Product Design*. John Wiley & Sons Ltd., 2021.

[9] E. Allen, “Keynote address: The essence of building technology,” in *Building Technology Educators’ Symposium*, D. J. Oakley and R. E. Smith, Eds., 2006, pp. 5–11.

[10] M. Davis, “Distinguishing architects from engineers: A pilot study in differences between engineers and other technologists,” in *Philosophy and Engineering*, 2009, pp. 15–30. Doi: 10.1007/978-90-481-2804-4_2.

[11] O. Tessmann, “Collaborative Design Procedures for Architects and Engineers.” Ph.D. dissertation, Books on Demand, 2008.

[12] M. Borrego and L. K. Newswander, “Characteristics of Successful Cross-disciplinary Engineering Education Collaborations,” *J. Eng. Edu.*, vol. 97, no. 2, pp. 123–134, Apr. 2008, doi: 10.1002/j.2168-9830.2008.tb00962.x.

[13] J. H. Lee, M. J. Ostwald, and N. Gu, *Design Thinking: Creativity, Collaboration and Culture*. Cham, Switzerland: Springer Ebook, 2020. [Online]. Available: https://link.springer.com/book/10.1007%2F978-3-030-56558-9

[14] A. Edmonds, T. Mourtis, and M. Boyle, “Parametric Design—A Drive Towards a Sustainable Future,” in *Innovation in Construction*, S. H. Ghaffar, P. Mullett, E. Pei, and J. Roberts, Eds., 2022, pp. 221–257.

[15] C. de Gaulmyn and K. Dupre, “Teaching sustainable design in architecture education: Critical review of Easy Approach for Sustainable and Environmental Design (EASED),” *Frontiers of Architectural Research*, vol. 8, no. 2, pp. 238–260, Jun. 2019, doi: 10.1016/j.foar.2019.03.001.

[16] J. Pallasmaa, The Thinking Hand: Existential and Embodied Wisdom in Architecture. Chichester, UK: John Wiley & Sons Ltd., 2009.

[17] L. Gul, “The impact of digital design representations on synchronous collaborative behaviour,” *J. Info. Tech. Constr.*, vol. 19, pp. 47–71, 2014.

[18] I. Anton and D. Tanase, “Informed Geometries. Parametric modelling and energy analysis in early stages of design,” in *Energy Procedia*, Bucharest, Nov. 2016, pp. 9–16. Doi: 10.1016/j.egypro.2015.12.269.

[19] M. Turrin, P. von Buelow, A. Kilian, and R. Stouffs, “Performative skins for passive climatic comfort,” *Autom. Constr.*, vol. 22, pp. 36–50, Mar. 2012, doi: 10.1016/j.autcon.2011.08.001.

[20] N. Gu, R. Yu, and P. A. Behbahani, “Parametric design: Theoretical development and algorithmic foundation for design generation in architecture,” in *Handbook of the Mathematics of the Arts and Sciences*, Cham: Springer International Publishing, 2021, pp. 1361–1383. Doi: 10.1007/978-3-319-57072-3_8.

[21] T. Wortmann and B. Tunçer, “Differentiating parametric design: Digital workflows in contemporary archi-tecture and construction,” *Des. Stud.*, vol. 52, pp. 173–197, Sep. 2017, doi: 10.1016/j.destud.2017.05.004.

[22] V. B. Arnaud, “Quantifying architects’ and engineers’ use of structural design software,” Master of Engineering, Massachusetts Institute of Technology, Boston, 2013.

[23] N. C. Brown and C. T. Mueller, “The effect of performance feedback and optimization on the conceptual design process,” in *International Association of Spatial Structures Annual Symposium*, Tokyo, Sep. 2016. [Online]. Available: https://www.researchgate.net/publication/316107726

[24] J. H. Lee, N. Gu, and M. J. Ostwald, “Creativity and parametric design? Comparing designer’s cognitive approaches with assessed levels of creativity,” *Int. J. Des. Create. Innov.*, vol. 3, no. 2, pp. 78–94, Apr. 2015, doi: 10.1080/21650349.2014.931826.

[25] R. Yu, J. Gero, and N. Gu, “Architects’ cognitive behaviour in parametric design,” International *J. Arch. Comp*., vol. 13, no. 1, pp. 83–101, Mar. 2015, doi: 10.1260/1478-0771.13.1.83.

[26] A. Stals, S. Jancart, and C. Elsen, “Parametric modeling tools in small architectural offices: Towards an adapted design process model,” *Des. Stud*., vol. 72, p. 100978, Jan. 2021, doi: 10.1016/j.destud.2020.100978.

[27] R. Oxman, “Thinking difference: Theories and models of parametric design thinking,” *Des. Stud.*, vol. 52, pp. 4–39, Sep. 2017, doi: 10.1016/j.destud.2017.06.001.

[28] A. Rolvink, R. van de Straat, and J. Coenders, “Parametric structural design and beyond,” *Int. J. Arch. Comp*., vol. 8, no. 3, pp. 319–336, Sep. 2010, doi: 10.1260/1478-0771.8.3.319.

[29] E. Touloupaki and T. Theodosiou, “Optimization of building form to minimize energy consumption through parametric modelling,” *Procedia Environ. Sci.*, vol. 38, pp. 509–514, 2017, doi: 10.1016/j.proenv.2017.03.114.

[30] Q. Liu, X. Han, Y. Yan, and J. Ren, “A Parametric Design Method for the Lighting Environment of a Library Building Based on Building Performance Evaluation,” *Energies (Basel)*, vol. 16, no. 2, p. 832, Jan. 2023, doi: 10.3390/en16020832.

[31] M. Stavric and O. Marina, “Parametric modeling for advanced architecture,” *Inter. J. Applied Math. Inform.s*, vol. 5, no. 1, pp. 9–16, 2011, [Online]. Available: https://www.researchgate.net/publication/285467523

[32] J. Beirão, P. Arrobas, and J. Duarte, "Parametric Urban Design: Joining morphology and urban indicators in a single interactive model," in *Digital Physicality Proceedings of the 30th eCAADe Conference – Volume 1*, H. Achten, J. Pavlicek, J. Hulin, and D. Matejovska, Eds., Czech Republic: eCAADe, Sep. 2012, pp. 167–175.

[33] P. Block, T. Van Mele, M. Rippman, and N. Paulson, *Beyond Bending: Reimagining Compression Shells*. Munich: Detail, 2017.

[34] D. Holzer, R. Hough, and M. Burry, "Parametric design and structural optimisation for early design exploration," *Int. J. Arch. Comput.*, vol. 5, no. 4, pp. 625–643, Dec. 2007, doi: 10.1260/147807707783600780.

[35] M. Tsigkari, A. Chronis, S. C. Joyce, A. Davis, S. Feng, and F. Aish, "Integrated design in the simulation pro-cess," in *Proceedings of the Symposium on Simulation for Architecture & Urban Design*, San Diego, Apr. 2013, pp. 153–162.

[36] N. Utami, "Design-work from home: Zoom as a video conferencing platform in architecture consultant firm," in *Proceeding International Conference on Information Technology, Multimedia, Architecture*, Design, and E-Business, 2020, pp. 102–109.

[37] P. Koutsabasis, S. Vosinakis, K. Malisova, and N. Paparounas, "On the value of Virtual Worlds for collaborative design," *Des. Stud.*, vol. 33, no. 4, pp. 357–390, Jul. 2012, doi: 10.1016/j.destud.2011.11.004.

[38] S. Ferguson, K. Lai, J. Chen, S. Faidi, K. Leonardo, and A. Olechowski, "'Why couldn't we do this more often?': exploring the feasibility of virtual and distributed work in product design engineering," *Res. Eng. Des*., Jun. 2022, doi: 10.1007/s00163-022-00391-2.

[39] M. Bassanino, T. Fernando, and K.-C. Wu, "Can virtual workspaces enhance team communication and collaboration in design review meetings?," *Arch. Eng. Des. Manag.*, vol. 10, no. 3–4, pp. 200–217, Jul. 2014, doi: 10.1080/17452007.2013.775102.

[40] L. F. Gül, “Evaluating design behaviour when using emerging collaboration technologies,” *Arch. Eng. Des. Manag.*, vol. 5, no. 3, pp. 107–123, Jan. 2009, doi: 10.3763/aedm.2008.0088.

[41] M. A. Rosenman, G. Smith, M. L. Maher, L. Ding, and D. Marchant, “Multidisciplinary collaborative design in virtual environments,” *Autom. Constr.*, vol. 16, no. 1, pp. 37–44, Jan. 2007, doi: 10.1016/j.autcon.2005.10.007.

[42] N. Cross and A. Clayburn Cross, “Observations of teamwork and social processes in design,” *Des. Stud.*, vol. 16, no. 2, pp. 143–170, Apr. 1995, doi: 10.1016/0142-694X(94)00007-Z.

[43] A. Dong, “The latent semantic approach to studying design team communication,” *Des. Stud.*, vol. 26, no. 5, pp. 445–461, Sep. 2005, doi: 10.1016/j.destud.2004.10.003.

[44] G. Goldschmidt, “The designer as a team o f one,” *Des. Stud.*, vol. 16, no. 2, pp. 189–209, Apr. 1995, doi: 10.1016/0142-694X(94)00009-3.

[45] D. Roy, N. Calpin, K. Cheng, A. Olechowski, A. Arguelles, N. F. S. Zurita, and J. Menold, “Designing Together: Exploring Collaborative Dynamics of Multi-Objective Design Problems in Virtual Environments,” *J. Mech. Des.* pp. 1-48, Oct. 2023, doi: 10.1115/1.4063658.

[46] K. Fu, J. Cagan, and K. Kotovsky, “Design Team Convergence: The Influence of Example Solution Quality,” *J. Mech. Des.*, vol. 132, no. 11, Nov. 2010, doi: 10.1115/1.4002202.

[47] J. J. Shah, S. M. Smith, and N. Vargas-Hernandez, “Metrics for measuring ideation effectiveness,” *Des. Stud.*, vol. 24, no. 2, pp. 111–134, Mar. 2003, doi: 10.1016/S0142-694X(02)00034-0.

[48] W. Zeiler, “The Difference in Communication Between Architects and Engineers and the Effectiveness within Integral Design,” in *Proceedings of the 16th International Conference on Engineering and Product Design Education*, Twente, The Netherlands, Sep. 2014, pp. 238–243.

[49] T. M. Amabile, “Social psychology of creativity: A consensual assessment technique.,” *J. Pers. Soc. Psychol.*, vol. 43, no. 5, pp. 997–1013, 1982, doi: 10.1037/0022-3514.43.5.997.

[50] K. K. Jeffries, “A CAT with caveats: is the Consensual Assessment Technique a reliable measure of graphic design creativity?,” *Inter. J. Des. Create. Inno.*, vol. 5, no. 1–2, pp. 16–28, Apr. 2017, doi: 10.1080/21650349.2015.1084893.

[51] J. H. Lee, M. J. Ostwald, and N. Gu, “Chapter 8: Design Thinking Across Borders,” in *Design Thinking: Creativity, Collaboration and Culture*., Springer Ebooks, 2020, pp. 191–209.

[52] S. Attia, J. L. M. Hensen, L. Beltrán, and A. De Herde, “Selection criteria for building performance simulation tools: contrasting architects’ and engineers’ needs,” *J. Build. Perform. Simul.*, vol. 5, no. 3, pp. 155–169, May 2012, doi: 10.1080/19401493.2010.549573.

[53] R. A. Wicklund and P. M. Gollwitzer, *Symbolic Self-completion*. New Jersey: Lawrence Erlbaum Associates, Inc., 1982.

[54] M. Kavakli and J. S. Gero, “Strategic knowledge differences between an expert and a novice designer,” in *Human Behavior in Design*, U. Lindemann, Ed., Berlin, Heidelberg: Springer Berlin Heidelberg, 2003, pp. 42–52. Doi: 10.1007/978-3-662-07811-2.

[55] S. Ahmed, K. M. Wallace, and L. T. Blessing, “Understanding the differences between how novice and expe-rienced designers approach design tasks,” *Res. Eng. Des.*, vol. 14, no. 1, pp. 1–11, Feb. 2003, doi: 10.1007/s00163-002-0023-z.

[56] S. M. Abdelmohsen and E. Y.-L. Do, “Analyzing the significance of problem solving expertise and computa-tional tool proficiency in design ideation,” in *CAAD Futures*, T. Tidafi and T. Dorta, Eds., 2009, pp. 273–287.

[57] B. Lucas and J. Hanson, “Thinking like an engineer: Using engineering habits of mind and signature peda-gogies to redesign engineering education,” *Int. J. Eng. Ped.*, vol. 6, no. 2, pp. 4–13, 2016.

[58] C. L. Dym, A. M. Agogino, O. Eris, D. D. Frey, and L. J. Leifer, “Engineering Design Thinking, Teaching, and Learning,” *J. Eng. Edu.,* vol. 94, no. 1, pp. 103–120, Jan. 2005, doi: 10.1002/j.2168-9830.2005.tb00832.x.

[59] H. J. Yazici, L. A. Zidek, and H. St. Hill, “A Study of Critical Thinking and Cross-Disciplinary Teamwork in Engineering Education,” In *Women in Industrial and Systems Engineering*, 2020, pp. 185–196. Doi: 10.1007/978-3-030-11866-2_8.

[60] A. Van den Beemt et al., “Interdisciplinary engineering education: A review of vision, teaching, and support,” *J. Eng. Edu.*, vol. 109, no. 3, pp. 508–555, Jul. 2020, doi: 10.1002/jee.20347.

[61] R. G. Hadgraft and A. Kolmos, “Emerging learning environments in engineering education,” *Australasian J. Eng. Edu*., vol. 25, no. 1, pp. 3–16, Jan. 2020, doi: 10.1080/22054952.2020.1713522.

[62] A. P. Ponzio, M. G. Gonzaga, M. P. de Castro, A. Vale, U. M. Bruscato, and W. Mog, “Parametric design learning strategies in the context of architectural design remote teaching,” in *SIGRADI 2021 Designing Possibilities Ubiquitous Conference*, 2021, pp. 1077–1088.

[63] D. J. Gerber and F. Flager, “Teaching Design Optioneering: A Method for Multidisciplinary Design Optimi-zation,” in *Computing in Civil Engineering*, Reston, VA: American Society of Civil Engineers, Jun. 2011, pp. 883–890. Doi: 10.1061/41182(416)109.

[64] C. Rodriguez, R. Hudson, and C. Niblock, “Collaborative learning in architectural education: Benefits of combining conventional studio, virtual design studio and live projects,” *British J. Edu. Tech.*, vol. 49, no. 3, pp. 337–353, May 2018, doi: 10.1111/bjet.12535.

[65] A. den Otter and S. Emmitt, “Design team communication and design task complexity: The preference for dialogues,” *Arch. Eng. Des. Manag.*, vol. 4, no. 2, pp. 121–129, Jan. 2008, doi: 10.3763/aedm.2008.0072.

[66] L. Luyten, “Architect and structural engineer communication in multi-disciplinary creativity,” in *The First International Conference on Structures and Architecture*, Jul. 2010, pp. 1793–1800.

[67] R. Rameezdeen and N. Gunarathna, “Comparison of cultures in consultant and contractor organizations in construction industry,” *Built-Environment-Sri Lanka*, vol. 3, no. 2, pp. 59–66, 2003.

[68] J. E. McGrath, "Method for Study of Groups," in *Groups: interactions and performance*, New Jersey: Prentice-Hall Inc., 1984, pp. 31–37.

[69] Shapediver GmbH, "Shapediver." Wien, Austria, 2019.

[70] C. Preisinger and M. Heimrath, "Karamba—A toolkit for parametric structural design," *Struc. Eng. Inter.*, vol. 24, no. 2, pp. 217–221, May 2014, doi: 10.2749/101686614X13830790993483.

[71] I. Chiu and F. A. Salustri, "Evaluating design project creativity in engineering design courses," In *Proceedings of the Canadian Engineering Education Association (CEEA)*, Jul. 2010, doi: 10.24908/pceea.v0i0.3088.

[72] R. R. Senescu, J. R. Haymaker, S. Meža, and M. A. Fischer, "Design process communication methodology: Improving the effectiveness and efficiency of collaboration, sharing, and understanding," *J. Arch. Eng.*, vol. 20, no. 1, Mar. 2014, doi: 10.1061/(ASCE)AE.1943-5568.0000122.

[73] M. Stevenson, J. W. M. Lai, and M. Bower, "Investigating the pedagogies of screen-sharing in contemporary learning environments—A mixed methods analysis," *J. Comput. Assist. Learn.*, vol. 38, no. 3, pp. 770–783, Jun. 2022, doi: 10.1111/jcal.12647.

[74] V. Abou-Khalil, S. Helou, E. Khalifé, M. A. Chen, R. Majumdar, and H. Ogata, "Emergency Online Learning in Low-Resource Settings: Effective Student Engagement Strategies," *Educ. Sci. (Basel)*, vol. 11, no. 1, p. 24, Jan. 2021, doi: 10.3390/educsci11010024.

[75] M. Schnabel, "Architectural parametric designing," in *Communicating Space(s): 24th eCAADe Conference Proceedings*, Volos, Greece, 2006, pp. 216–221.

[76] S. Senaratne and S. Gunawardane, "Application of team role theory to construction design teams," *Arch. Eng. Des. Manag*, vol. 11, no. 1, pp. 1–20, Jan. 2015, doi: 10.1080/17452007.2013.802980.

[77] J. H. Lee, M. J. Ostwald, and N. Gu, "Introduction: exploring design thinking," in *Design Thinking: Creativity, Collaboration and Culture*, Springer Ebook, 2020, pp. 1–32

# Chapter 5

## Characterizing Student Designerly Behavior in Optimization Tools

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### Abstract

Parametric optimization techniques allow building designers to pursue multiple performance objectives, which can benefit the overall design. However, the strategies used by architecture and engineering graduate students when working with optimization tools are unclear, and ineffective computational design procedures may limit their success as future designers. In response, this research identifies several designerly behaviors of graduate students when responding to a conceptual building design optimization task. It uses eye-tracking, screen recording, and empirical methods to code their behaviors following the situated FBS framework. From these data streams, three different types of design iterations emerge: one by the designer alone, one by the optimizer alone, and one by the designer incorporating feedback from the optimizer. Based on the timing and frequency of these loops, student participants were characterized as completing partial, crude, or complete optimization cycles while developing their designs. This organization of optimization techniques establishes reoccurring strategies employed by developing designers, which can encourage future pedagogical approaches that empower

students to incorporate complete optimization cycles while improving their designs. It can also be used in future research studies to establish clear links between types of design optimization behavior and design quality.

### *Practical Applications*

Increasingly, building designers use digital optimization tools to explore and improve designs. This research identifies and categorizes several distinct design behaviors when using optimization tools that have not been previously recognized. Applying these categories to describe graduate student designer behavior allows educators to find opportunities for improving design education. While there is no set standard for how optimization tools should be used, different strategies range in the potential they create for simulation feedback to improve the design. Although all study participants were able to implement an optimization feature, they did not all fully integrate the feedback into their design decisions. From this research we observe that it is not enough to explain algorithms and show a student how to run an optimization tool, but these tools must be taught in the context of robust design approaches. Educators wishing to identify their students' design strategies can use the methods and language established in this paper to assess student comprehension of optimization techniques. Future work can apply the behaviors that investigate other dimensions of optimization in design, such as design quality and comparing categories of designers.

## 5.1 Introduction

As digital tools evolve, emerging computational strategies allow designers in the Architecture-Engineering-Construction (AEC) industry to address an increasing number of building performance criteria early in the design process. In particular, parametric design strategies, where a model is readily edited and explored by editable variables, enable AEC designers to rapidly consider numerous potential options while meeting disciplinary goals. Within parametric models, optimization techniques can systematically find the best options in terms of quantitative design goals such as energy use or structural efficiency [1], [2]. However, there is uncertainty about how to best apply optimization during design, especially for emerging interactive optimization approaches that let designers manage qualitative and quantitative goals simultaneously. Optimization can speed up certain design subtasks, and it can help find high-performance solutions within a design space that might be difficult to find otherwise [3]. Yet it also requires a designer to formulate, analyze, and in some cases iterate a defined set of variables, objectives, and constraints, which may change the timeline or nature of activities in a typical design procedure.

While there is considerable established literature describing designer behavior in general, little is known about how diverse optimization tools influence design, particularly in the domain of architectural engineering education, as students gradually learn how to incorporate optimization. One source of potential confusion stems from the range of design tools that are described as employing optimization, especially in practice. On the one hand, some define “design optimization” very broadly as the process of systematically and quantitatively improving on a current solution, as in the case of building simulation [4]–[6]. On the other end of the spectrum, some only use the term “optimization” to refer to numerical simulation and/or formal mathematical optimization [7], [8], even in the context of building design. In the middle are heuristic techniques such as evolutionary algorithms that designers might implement alongside their own qualitative preferences, either a priori, a posteriori [9], or interactively [10]–[12]. In all cases, the designer is left to establish their own sequence and timing for establishing the parametric variables and their relationships in the first place. If instructed to formulate their own design spaces and optimize a design, students might employ any of these approaches, with various degrees of completeness or effectiveness. Yet the characteristics of these ranging strategies have not been established.

In response, this research asks: what patterns of design behaviors do architecture and engineering graduate students employ while constructing and exploring a parametric model using optimization-based tools? Potential patterns include iterative decision loops involving the designer, an automated algorithm, or both, as well as their timing and frequency within a design session. Investigating how this group of designers, who are neither novices nor experts, utilize different optimization techniques can inform which strategies they employ with optimization tools. To investigate design in situ, a research study was conducted which asked participants to create a visually appealing atrium enclosure that addressed measurable concerns of daylighting, energy use, and structural performance. Eye-tracking data, screen recordings, and observational assessment were used together to apply the situated FBS framework [13].

This framework allowed for identifying multidimensional steps in the design process, describing design session events, and discerning varying strategies among the participants. The student participants showed a range of behaviors in their use of optimization techniques —some spent considerable time formulating the problem and used optimization techniques near the end of the design session, while others adjusted the problem more frequently as they ran smaller iterative explorations. These diverse strategies are used to distinguish several distinct design iteration types and corresponding behaviors that are detailed in the results and discussion. In understanding the rich characteristics of designer strategies through qualitative methods, we can first discern these behaviors through deep analysis before future quantitative studies establish their prevalence among designer populations.

## 5.2 Background

The AEC professions are continually tasked with providing high performing solutions, but the numerous considerations in building design rarely align. To manage potentially competing objectives, designers have incorporated computational exploration and optimization tools, which can account for multidisciplinary performance, to make more informed design decisions. While the feedback and guidance from these emerging design approaches can improve outcomes, designerly strategies for utilizing optimization in the context of design theory have yet to be thoroughly examined. In particular, the optimization patterns of intermediate designers, such as graduate level architecture and engineering students who have experience with design strategies but are still developing their optimization skills, are largely unknown.

### 5.2.1 Designerly Behaviors in the Design Process

To systematically characterize designer behavior when using optimization tools, and to determine how these tools potentially alter traditional processes, it is first necessary to ground the research in a conceptual framework for design behavior. Although design is a complex series of decisions, researchers have identified general characteristics of the design process [14]–[17], which are used to recognize reoccurring design strategies. Most of these models establish a phase for problem definition, one for design development, and one for solution analysis, with opportunities for iteration throughout. However, these models are very broad in their scope.

Several researchers have considered characteristics of design behaviors when working collaboratively with computation tools [18], particularly in the medium of parametric modeling [19]–[22]. Literature shows that when a computer is used to support or make key decisions, there are different schemes by which to identify a designer's cognitive or computational decisions [20],

[23], [24]. In some cases, incorporating parametric modeling and rule-based digital software can improve the efficiency of design [25], [26]. However, other research has differentiated that parametric modeling is still the result of a tool and cannot replace the ingenuity of a human designer [27]. In fact, precedent study observations show that in practice, parametric design focuses on more controlled, rule-based designs rather than a vast multitude of solutions [28]. This narrowing of potential designs based on designers' knowledge and intuition may also be evident in optimization strategies.

While these prior investigations of parametric design strategies inform aspects of this paper, we based our optimization-related study on the situated FBS framework [13], which is an extension of the fundamental and widely applied FBS ontology [29]. Gero's original ontology has been used by many design disciplines to model, code, and analyze design behaviors [30]–[32]. It models the design process by first assigning the characteristics of the desired artifact into three primary categories: function (the role of the artifact), behavior (how the artifact performs), and structure (the qualities of the artifact). The development of these characteristics is identified by eight types of fundamental design moves, which create a framework to define the design process. However, although the original FBS provided a clear foundation to describe a range of design tasks, it did not account for the influence of cognitive context on design.

In response, Gero and Kannengiesser [13] present a revised method called the situated FBS framework (Figure 5-1), which considered an additional, recursive dimension of design: the conceptual environment. This new framework expanded the original 8 processes into three conceptual environments: an external world, an interpreted world, and an expected world. By dividing the FBS elements into each world and categorizing the processes as an action, interpretation, or focusing, the situated FBS framework provides a more extensive strategy by which to map the evolution of the design process. For example, within the synthesis, analysis, and evaluation processes, an expected behavior (Bei) motivates the designer's idea for a structure

(Sei) (process 11), which the designer then represents that structure externally (Se) as a sketch or 3D model (process 12). Next, the designer considers whether the representation aligns with their idea (process 13). Simultaneously, that structure produces an associated behavior (process 14), which the designer can compare to the expected behavior (process 15). If considered adequate, the designer can proceed to documentation, or they may repeat the processes going as far back as reframing Functions (process 16).

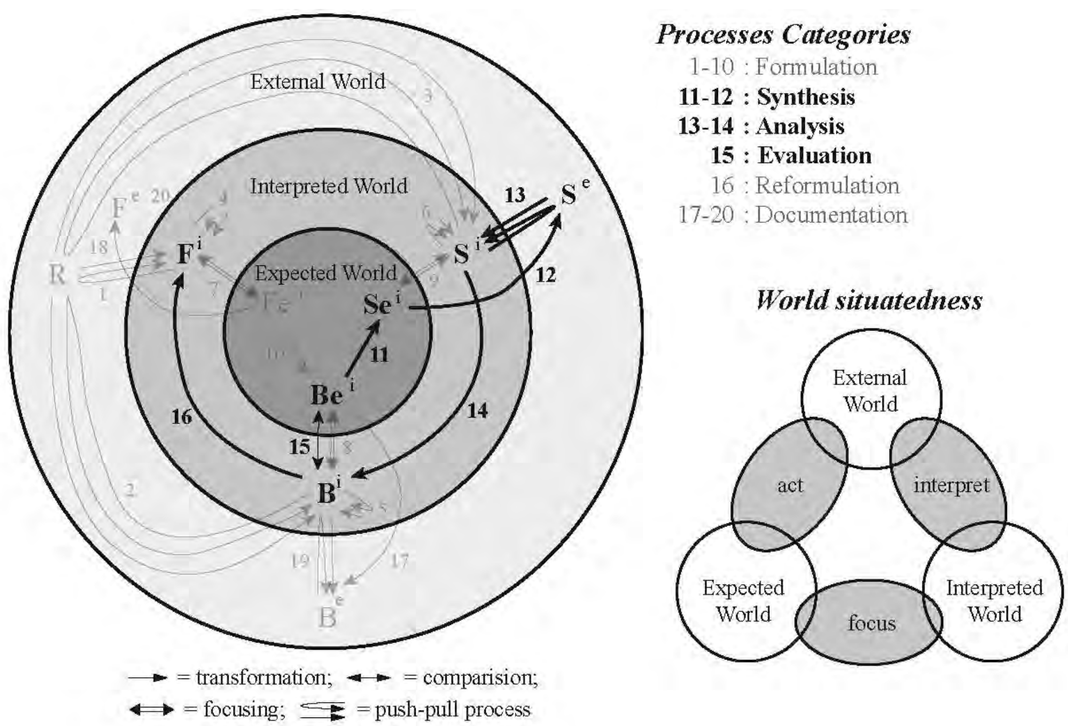


Figure **5-1**. Situated FBS framework with emphasis on the processes focused on in this paper, and the situatedness and interaction of three worlds, after concepts of Gero and Kannengiesser [13].

With this framework, design researchers can incorporate more comprehensive modeling of iterative thinking and the regeneration of ideas. Even with these adjustments, the FBS ontology has been criticized for its ambiguity [33], [34] while others emphasize FBS's applicability [35]. Nevertheless, the FBS ontology has been used to model design in many disciplines [36], [37], including parametric building design [38]. Its expanded version, the situated FBS framework, also presents several advantages for this study of optimization strategies. It provides an order by which to identify design events and organizes the relationships between the designer's ideas, the behavioral bounds of the design, and the realization of the design artifact. It also acknowledges the iterative loop between what the designer envisions and what manifests externally (shifting between the 3 worlds), which can occur in parametric, rule-based design exploration.

Parametric design tools have been shown to help designers produce unconventional solutions [24], [28], some of which may not have been originally conceived by the designer. The uniqueness of the designs and potential for innovation have been assessed by traditional methods for measuring creativity and shown that parametric thinking is a viable form of design [39]. In addition, this method of idea generation prompts consideration of a designer's source for decision making. In Yu et al.'s study [38], the researchers defined a subset of characteristics in the FBS ontology and classified the designer's decisions as either "design knowledge" or "rule algorithm" to differentiate the source of cognitive effort throughout the phases of the design session. We also identify subsets of decisions within the situated FBS framework in this paper to codify the participants' design process and identify design events unique to optimization. Differentiating between decisions focused on developing the artifact or developing the optimization approach is valuable in evaluating computational design behaviors, especially as the use of digital tools to solve complex building challenges becomes more pervasive.

### 5.2.2 Building Optimization as a Design Technique

As the performance needs of our built environment grow more stringent, it is increasingly difficult to address multiple design considerations across a range of professional specialties. Although achieving an effective, holistic design is advantageous, building performance criteria vary in units, scale, and importance, making them difficult to empirically compare and optimize [1], [40]. For example, the benefits of increasing natural daylight with more windows can compete with the goal of reducing energy consumption. Building optimization quickly becomes convoluted as there are many numerical and experiential criteria, such as spatial, structural, and mechanical objectives [2]. Furthermore, when AEC disciplines collaborate on optimization projects, it has been shown that an iterative process emerges between the designers and their optimization tools [41].

Traditionally, designers relied on knowledge to find effective solutions, but computational tools allow designers to rapidly explore a range of solutions with quick performance feedback, enabling more efficient production of high-performance designs for architects and engineers [10], [42], [43]. However, some designers criticize digital design space exploration for its limitations in design thinking and potential design fixation compared to traditional sketching processes [44]. Nevertheless, optimization has been utilized by a variety of engineering disciplines with advantageous results [2], [45], [46] and research has shown that the use of computational tools is a viable method for design in AEC [10], [11], [47]. In particular, the applicability of optimization in computer aided architectural design has been suggested early in the development of building computation simulation [48]. However, due to the emerging nature of optimization tools, the best practices for their use are still being defined. At this point, strategic optimization education can impact the effective implementation of such tools by graduate designers and is not unique to just optimization.

### 5.2.3 Student Designers Working in Digital Tools

It has been suggested that parametric design is advantageous to the development of a designer because it prompts the setting of constraints on a design task to find different solutions rather than focusing on one solution [49]. Yet students may be limited in their ability to fully execute a design since they are still developing as designers themselves and are still mastering design tools [50]. In addition, curriculum standards in building design education vary by discipline, and the influence of pedagogical systems on problem-solving strategies are somewhat unpredictable [51]. Specific to optimization pedagogy, recently developed courses in architecture and engineering programs have introduced optimization to students with promising initial results [52]–[54], but the learning outcomes of these courses are not standardized, and the tools and processes used vary by institution. Nevertheless, much of the emerging research that considers early-stage optimization tools focuses on student participants [43], [55]–[57], so there is value in identifying specific sources of student limitations in design environments, particularly for optimization.

Considering this population, it has been shown that novice designers tend to use less sophisticated processes compared to experts [58], [59], which may hinder effective use of optimization methods. Intermediate designers, though, such as graduate-level architect and engineer students, represent a stage in education development in which designers possess a foundation for disciplinary design decisions and have experience working with design tools, but are still developing as effective problem solvers. Identifying graduate student designer strategies while they make decisions with optimization tools may help categorize effective behaviors, improving tools for design development, and enhance learning processes for graduate students as future experts. Accounting for the context of proliferating digital tools in AEC, this research focuses on optimization behavior in conceptual building design.

## 5.3 Methods

This IRB approved study asked graduate-level architect and engineering design students to propose an optimized solution in response to a conceptual building design task. The multi-method research design employed eye-tracking, screen recordings, and interviews to capture different streams of data from the design sessions. Observational data analysis and artifact analysis techniques were used to qualitatively code the design segments within the situated FBS framework. Our analysis protocol was also employed to identify designerly events unique to optimization, relating reoccurring behaviors between designers to potentially effective optimization strategies.

### 5.3.1 Participants

The streams of observational and interview data were collected from a sample size of 10 architecture (5) and architectural engineering (5) graduate students at a research-intensive public university in the northeastern United States. This population is of special interest to understand the design practices of designers at an intermediate educational stage rather than those of novice undergraduates (who typically have not developed either design or engineering skillsets) or practitioners (who are fully expert in their designerly ways). While this sample size may seem small, each participant generates 3 hours of video screen capture data, eye-tracking data, and interview data, supporting a multi-stream qualitative study. This amount of data is quite large and rich considering the purpose of this study is to identify and characterize the types of optimization behaviors rather than conduct predictive or generalizable statistics. Participants included 6 women and 4 men. They were recruited by email announcement of the study to the architecture and architectural engineering department and were compensated with a $20 gift card. The participants completed a survey before beginning the design task and reported at least 1 year of experience (average 3.5 years) and a moderate level of confidence with the study's modelling tools, along with at least 1 year of experience in optimization. Amount of time spent in design practice among participants, which can occur before or during the pursuit of graduate degrees, ranged from 0-10 years. By studying graduate-level designers, we elicit a deep understanding of how the design learning process occurs as architects and engineers move past their novice design tendencies.

### 5.3.2 Design Session

All design sessions were conducted in a controlled research space equipped with a computer, eye-tracking hardware, and software. The research procedure is shown in Figure 5-2. After the participants were situated at the computer, they were briefed on the design task through a standard video introduction and their eye-tracking setup was calibrated for their sitting position. After watching the design task video, but before working in the digital space, the designers were provided with paper and pencils to take notes or sketch on paper for 5-10 minutes, which enabled them to create initial ideas separate from the model space. They then proceeded to work in the digital modeling tools to develop their design and produce optimized solutions. The designers were prompted to work for as long as they felt comfortable, resulting in sessions that lasted approximately 3 hours.

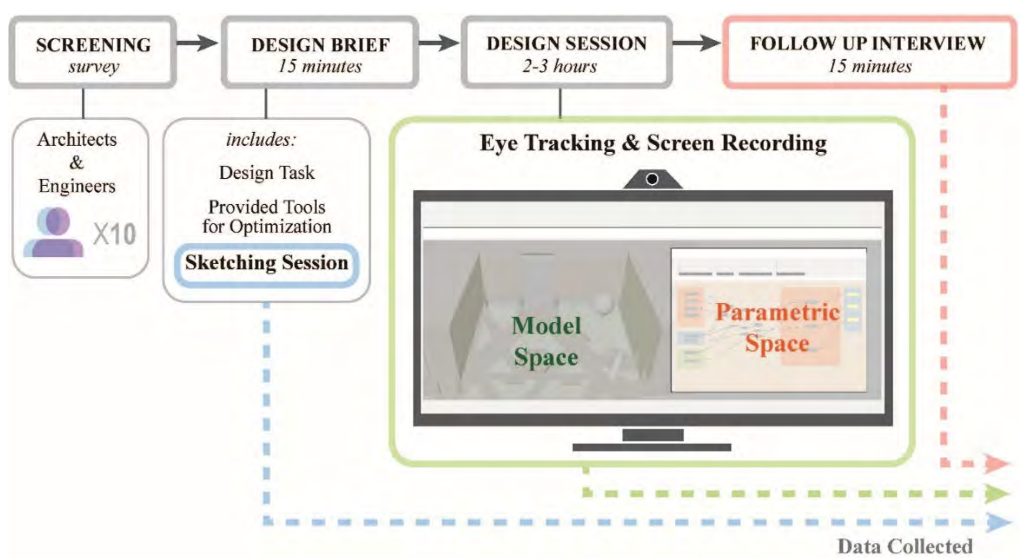


Figure **5-2**. Summary of the events in a design session, showing the data that was collected, and a preview of the digital design interface.

While Grasshopper in Rhinoceros was used as a consistent parametric modeling platform, the designers were able to choose their own optimization plugins, since the application of these tools is a part of authentic design behavior. In this study, the participants preferred using either Galapagos [60], presumably adding their own prioritization mechanism to manage multiple objectives or Design Space Exploration's Multi-Objective Optimization tool [42] to find optimized solutions. Notably, both tools preview intermittent design iterations while running, such that designers can make visual assessments before the tool has completed its optimization loop. It is also worth noting that these chosen tools do not fully enable interactive human-in-the-loop optimization at the scale of design generations or internal dynamic data visualization, which are possible using newer or less common parametric tools, such as Stormcloud [61], Wallacei X [62], and Stepper [63]. Full documentation of design strategies with these tools would require future analysis.

The participants could repeatedly use their optimization tool in the session if they wished, but they were not explicitly prompted to do so. After settling on a final design, the designers were asked to submit 2-4 screenshots of their proposal and a written design statement to give to a fictional client. Immediately following submission of their deliverables, the researcher interviewed the participants using a semi-structured interview protocol, asking about their goals for their design, how they approached completing the design, and what they would do differently if they had more time. The interviews were used as cognitive proxies to contextually ensure that behaviors were correctly interpreted.

### 5.3.3 Design Task

The design task asked participants to develop a glass atrium infill for a fictional university client in Phoenix, Arizona. This site was chosen because of the region's hot and sunny summer climate, which is easily recognized or readily learned in an online search. A university setting was used for site context to prompt the need for visually exciting designs, and for its accessibility to the participants. The design task required the designers to address at least two of three provided objectives. The first objective is to maximize daylighting during the summer solstice (June 21) at noon. While building designs often consider daylight at multiple times throughout the year, full daylighting simulations can take hours or even days to run. Focusing on a significant instance in time is a common design strategy that eliminates wait times and reduces required computation power. The second goal is to minimize solar radiation. Within the task, reducing the surface area of the atrium will reduce solar radiation, as will substituting thicker glass or opaque panels with better u-values. The third objective is to minimize the elastic energy of the structure, as calculated by Karamba3D [64]. It is desirable to have a structure with less deflection because it will allow for smaller members to build. Reducing structural weight can also reduce costs. Optimizing a whole structural system is a complex task but asking the designers to focus on two of these three goals provides a conceivable and numeric goal for them to manage in the constraints of this conceptual design task.

The designers were given the design task through two introduction videos. In the first video, the fictional client showed four example atriums that the university admires. Although providing examples to the participants may bias their design solutions and prompt them to imitate what they are shown [65], clients often share their visions for a project during an authentic design process in practice. Providing participants with examples of atriums also frames the design task in terms of parametric thinking, which was the intended design environment of this study. However, before introducing the designers to the study’s computational tool, participants were allowed to sketch or write out initial ideas, permitting them to first consider ideas not constrained to the computational environment.

Participants were also provided with a base file containing the site context, important points of reference, and pre-built scripts that calculate the objectives. The script required that the participants provide surfaces for the intended solid panels, surfaces for the glass panels, the structure represented as lines, and the structural support points. In this way, the designers could focus their efforts on working towards an optimized solution, and the study was given a consistent frame for simplified performance simulation between the designers. Moreover, this study focuses on optimization tactics, not on the designer's ability to assemble a structural analysis simulation.

### 5.3.4 Qualitative Coding and Characterization of Design Behaviors

During the design session, the participants' behaviors were captured by screen recording and tracking their eye gaze data using EyeWorks eye-tracking hardware [66]. Eye tracking, combined with screen capture recordings, is a robust method to understand design behaviors because it offers the ability for researchers to not just capture outcomes, but also actions and patterns of behaviors paired with information about what the participant is looking at or turning their attention toward. These types of data are highly complex, with each minute of participant behavior resulting in hundreds if not thousands of potential data points for each participant generated over a ~3 hour design task.

The researchers also observed the design session to record times when the participant sketched or encountered difficulties with the tool, and to facilitate an immediate follow up interview about the participant's rationales for critical design decisions. The follow up interviews asked the designers to elaborate on their design decisions and what difficulties they encountered. They were also asked, if given more time, what would they do differently to further refine their design.

#### *5.3.4.1 Data Analysis*

To analyze the streams of data, various methods were employed. First, the video recordings were reviewed and activities that did not pertain to the design session were removed, such as saving and restarting the program. Second, the eye-tracking data were initially analyzed using digital tools to interpret broad patterns in participant behavior. Using additional software from EyeWorks, the eye gaze data was paired with two Regions of Interest (ROI) on the screen to identify if the participant looked in the parametric space (Grasshopper), the 3D modeling space (Rhino), or away from the screen altogether. These tools help interpret the digital information representing design behavior.

When working in these tools, a designer develops their model by programming geometry in the parametric space and viewing their model in the 3D modeling space. While these regions stay the same for each participant, the displays inside the regions are dynamic as participants rotate or zoom in on the design or pan across their script. Thus, a significant dwell time in an ROI shows either consideration of the design artifact or computational manipulations of the design. Figure 5-3 shows where the two ROI's are on the screen (the 3D modeling space and the parametric space), a preview of what may be displayed in the spaces, and a brief description of what occurs in the spaces. Eye tracking was thus required to accurately identify loops between Regions of Interest, which eventually helped define behaviors.

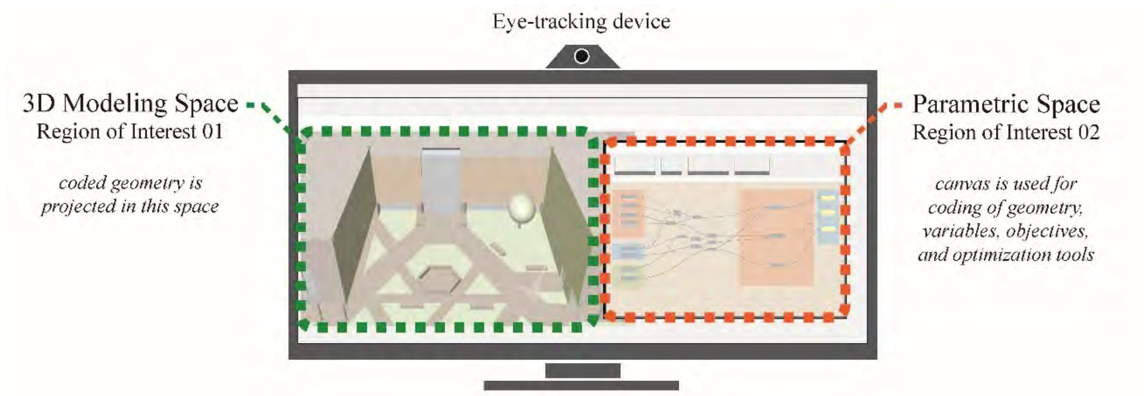


Figure **5-3**. Two regions of interest (ROI) on the screen and descriptions of the regions.

The output video files from the eye-tracking data were analyzed using observational qualitative data analysis processes, called "coding," honed for observational and time-resolved research to characterize design behaviors. These methods work abductively from existing frameworks for design cognition to accurately describe the breadth of behaviors observed [67]. A codebook describing the names and definitions of the design activities, which could be categorized, was developed through literature and piloted iteratively on the data in consensus with the other members of the research team and strongly grounded in design theory. After this iterative codebook was developed, a single researcher rewatched all the design sessions and notated the presence of every design behavior and their time stamps. The coding comprised of elements from the situated FBS framework in identifying the iterative process between Function, Behavior, and Structure in the context of the optimization environment. The typology of behaviors captured, aggregate percentages of behaviors captured over time, and the ordering in which behaviors occur through the duration of the design challenge are used to answer the research question related to patterns of design behaviors.

The interview recordings were employed as an external validation method to ensure that the research team was interpreting behaviors accurately, particularly for critical decisions, but were not independently thematically analyzed for this study. The interview questions are provided in Appendix F. Together, the multiple streams of qualitative data (screen recording, eye tracking, and interview transcripts) are used to inform the interpretation of the behaviors as they relate to architectural engineering design education.

#### *5.3.4.2 Event Codes*

We determined 13 events of behavior that manifested across all ten participants. Figure 5-4 shows the coding of events in the situated FBS framework to the conceptual optimization process. The code also highlights several concrete events identified in this study, which define the behavioral structure of the individual sessions. The sessions were divided into two primary phases, “pre-modeling” and “modeling,” which are determined by the placing of a first component in Grasshopper. Placing the first component is coded as a process 12 in which the designer manifests their idea for an artifact in the external world. In this study, the pre-modeling phase is mostly rapid formulation (processes 1-10), and although sketching in the Pre-modeling phase is also a process 12 since it allows the designer to externalize their ideas onto paper, the formulation processes are informally executed and not within the scope of this paper.

| Process Group | Process | Discription | Events |
|---|---|---|---|
| Formulation | 1-10 | Internalizing design task; developing $Be^i$ and $Se^i$ | Pre-modeling process |
| Split Pre-modeling phase and Modeling phase | | | Placing first component |
| Synthesis | 11 | Envisioning solution from $Be^i$ to $Se^i$ | Event happens internally |
| | 12 | Externalizing envisioned Se to external $S^e$ | Developing design in grasshopper* |
| | | $S^e \to S^V$ | Introducing a variable |
| | | $S^e \to S^S$ | Sketching again |
| | | $S^e \to S^P$ | Defining solid and glass panels |
| | | | Plug in elements to objectives |
| Analysis | 13 | Considering if external $S^e$ aligns with Se | Reviewing design in model space** |
| | 14 | The resulting $B^i$ from $S^i$ sdf | Running optimization tool |
| Evaluation | 15 | Interpreting if $B^i$ meets $Be^i$ | Reviewing optimization results |
| | 16 | Changing $F^i$ based on $B^i$ | Changing which objectives they pursue |
| Documentation | 12 | | Editing representation of design |
| | 17-20 | Shifting from expected and intepreted into external | Writing about design |

*Defined by looking in the Grasshopper canvas
**Defined by looking in model space for more than 0.5 seconds

Figure **5-4**. Coded behaviors in this study from the situated FBS framework.

### *5.3.4.3 Synthesis Events*

We also captured the occurrence of "synthesis events" as a manifestation of the processes. Synthesis events include a process 11, which is envisioning solutions (Sei) from formulated behavior (Bei), and process 12, which is externalizing the solution. In this study, process 11 was an internal decision, so this step was not explicitly captured. However, synthesis process 12 accounts for many of the designer's actions and was divided into 4 categories to better describe the designer's externalized decisions. Most of the actions in the parametric space that create structure (Se) are when the designer places a static component, but there are other events which relate directly to the optimization process. Following precedent from Yu et al. [38], which divided Function, Behavior, and Structure into knowledge-based and rule-based cognitive decisions, this research identified 3 events within process 12 in this study: the introduction of a variable to the model, a return to sketching on paper, and the defining of solid and clear panels.

Introducing a variable suggests the potential for that element to be influenced by optimization feedback. Notably, not all the variables created in each session were used in the optimization events, which turns them into parameters in formal optimization language. Overall, individual narratives concerning the use of variables inform each designers' process. The process 12 event of "returning to sketching" is also not always present in every session, but it is determined when a designer looks away from the screen and picks up their writing utensil. All designers created surfaces in their design and discerned between solid and glass panels. Until this event occurs, their design decisions are geometric and do not considered materiality, which is a Behavior aspect of the design.

#### *5.3.4.4 Pre-analysis and Analysis Events*

Other definitive events in this study are when participants first plug elements into the objective value generators and when they first activate their optimization tool. Shifting to the generator signifies a transition from relying on design knowledge to preparing for optimization feedback. The designers may return to design knowledge after interacting with the objective generator, but this is an event unique to the optimization process, and the timing of its occurrence in the session informs how integral the designers see optimization in their final solution. To meet the requirements of the objective generators, they may also have to restructure part of their model, relying on a mixture of design knowledge and parametric knowledge.

A further indicator is when the designer starts preparing the optimization tool to optimize the design. This is not always an efficient process, particularly for the student designers, as the planning for optimization sometimes prompts reevaluation of design variables. Once the optimization tool is run, a series of analysis, evaluation, and synthesis processes (13, 14, 15, and

12) occur between the designer and optimization tool from which the designer can make a design decision.

#### *5.3.4.5 Evaluation and Documentation Events*

Before proceeding to documentation, a designer will verify if the behavior of the design meets the expected behavior. In early conceptual design development, this process is largely driven by the optimization tool, which minimizes the objective values. However, the designer may consider the results manually and decide to repeat earlier processes or proceed to documentation. In some cases, a designer may follow process 16, which is an opportunity to change the function of the design by changing which of the two objectives they wish to pursue. This process did not occur in this study's design sessions.

The final event defined in this study is the shift to documentation. This is defined as when the designer opens the writing document and begins to compose their design statement or take screenshots of their final design. In some cases, the designers refine the representation of their design in preparation for documentation, such as applying color to the different panels.

### 5.3.5 Evaluation of Designer Behavior

Coding and identifying these processes allowed the design team to compare reoccurring behaviors, design focus, and significant events. In following the situated FBS framework, a series of repeated actions are identified in the conceptual design optimization sessions. While Gero and Kannengiesser acknowledged types of design "Reformulations," this research identifies iterations performed by the designer, by the optimizer, and by the designer and the optimizer together, shown in Figure 5-5. Prior to running the optimization tool, the designers ran through process 11, 12, and 13, in a series of iterative loops. These loops were identified by the designers' dwell time in the Grasshopper canvas and the modeling space, as recorded by the eye-tracking tool.

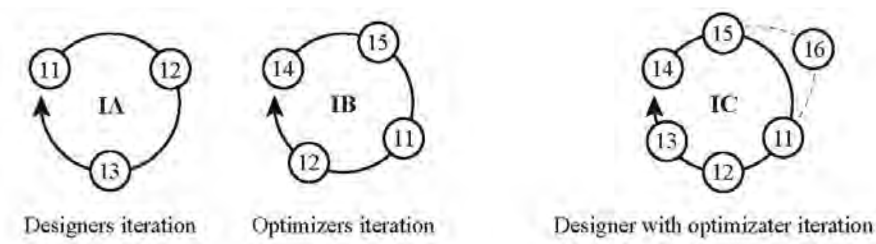


Figure **5-5**. Illustration of the identified iteration loops including iteration loop A (IA), iteration loop B (IB), and iteration loop C (IC).

Appropriate dwell times are often determined by the task context [68] and are difficult to standardize [69]. While eye tracking has been used in many areas, its application in 3D architectural modeling tools is less common. Dwell times that are measured in milliseconds tend to correspond to small Areas of Interest, like a button on a webpage. However, this research uses Regions of Interest that correspond to how participants consider the design versus manipulating the design script. Both activities likely require dwell times in the small number of seconds, which have also been considered in relation to programming activities [70]. Frequency of looking at the regions is significant, as iterative loops were identified at the resolution that patterns emerged for the design sessions. Based on researcher experience with the design tools and iteratively testing different timeframes, the sessions were divided into 0-4 seconds, 4-12 seconds, and 12+ seconds. Glancing in the model ROI for less than 4 seconds was determined to be a "check" that the Grasshopper command was doing the intended purpose, rather than a responsive assessment of the design associated with a process 13. Looking at either region for longer than 12 seconds indicated that the designer was focusing on component assembly in Grasshopper (ROI2) or reflecting on the representation of their model (ROI 1). An Iteration Loop A (IA) was determined when the designer looked back and forth between Grasshopper and the modeling space at least once, for 4-12 seconds in each region. IA loops can be counted, providing a metric by which to compare the designers' iterative behaviors.

The second Iteration loop is performed by the optimization tool, Iteration Loop B (IB), starting from process 14 to 15, 11, and 12. It runs through these rapidly and iteratively until stopping back at Bi. Notably, the optimization tool does not perform process 13, as it cannot consider if the external structure aligns with the designer's interpreted structure. After running the optimizer, the designer may continue to move through synthesis, analysis, and evaluation processes based on abstract goals, or move directly onto documentation. If they respond to the optimization feedback and make adjustments, then that is considered an Iteration Loop C (IC). This iterative process is similar to the interactive behavior identified by Geyer et al. [41] as a designer works back and forth between design modeling and optimization.

These iteration loops allowed us to identify how early the designers ran their optimization tool in the session, what processes they followed after reviewing the results, and if they repeated the optimization. IA loops were identified automatically based on relationships in the eye-tracking data. Although IB and IC loops contain defined actions, not open to interpretation or variation of researcher perspective, they did require manual recordings of when a certain component was placed, connected, or manipulated in the screen recordings. A member of the research team reviewed the sessions twice to verify that the processes were accurately identified. The occurrence of the iteration loops, types of Structure moves, and optimization events produce narratives that enable comparison between participants.

## 5.4 Results

Based on the coding structure, simplified session time plots are shown in Figure 5-6. The sessions are divided into Pre-modeling and Modeling phases. The beginning of the Modeling phase is marked with “0 minutes.” The horizontal line in each diagram is the session timeline from sessions beginning to end. Along the timeline, the IA (Designers) loops are plotted, showing their occurrence and duration. Similarly, below the timeline, iteration types IB (Optimizers) and IC (Designer with optimizer) are shown with blocks, indicating when and for how long each loop lasted. Above the timeline, significant events within the optimization process are also labeled according to their triggers in the previous section. Plugging their design into the objective value generator (“obj.”) represents an active, cognitive engagement with the design objectives. Later in each session, the opening of an optimization tool and preparing to run it (“prep optimizer”) is considered the beginning of the optimization process. At the end of each timeline, the time spent documenting the design is shown as a thicker gray band.

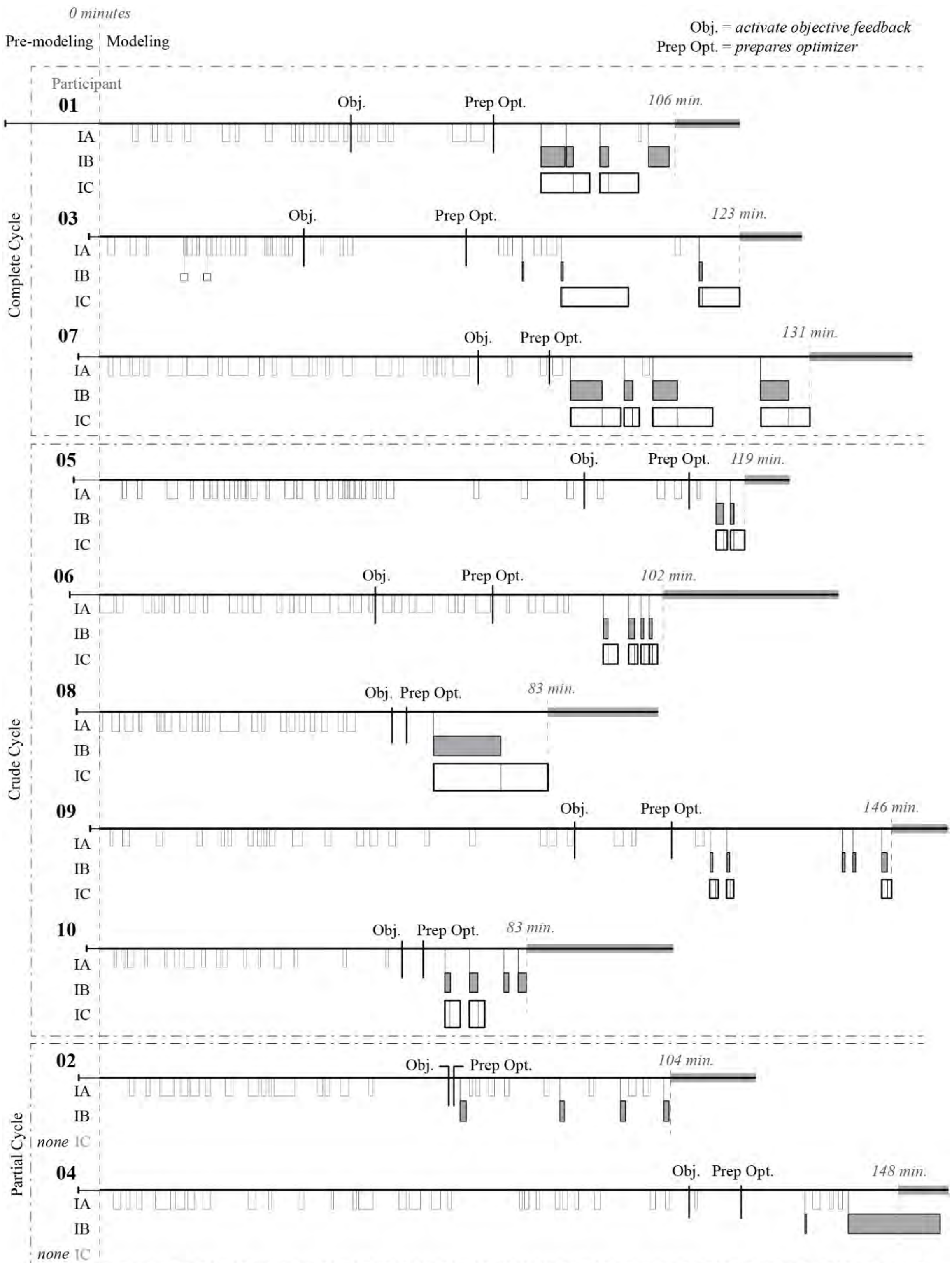


Figure **5-6**. Design session behavior time plots.

The sessions are organized by three categories of optimization behavior, as determined by reoccurring characteristics. A “Complete Optimization Cycle” is when the participant completed at least one full IC iteration and there is evidence of informed edits to their design, such as the presence of an IA iteration after optimizing or a substantial amount of time spent considering results. A “Coarse Optimization Cycle” is when the designers completed at least one IC iteration, but the cycles did not influence any notable changes in the design. The third cycle, a “Partial Optimization Cycle,” is when the designer did not complete a full IC iteration, meaning they did not consider the best performing suggestions from the optimization tool. Although the cycle categories do not indicate the quality of design idea or the efficacy of resulting design performance, they do organize a system by which to understand optimization techniques and discuss nuances between behaviors. The next three sections describe in detail representative participants for each type of cycle.

### 5.4.1 Complete Optimization Cycle

The Complete Optimization Cycle participants closely followed an expected optimization process in which a designer integrates behavioral (process 14 and 15) considerations in the development of their design and completes at least one full designer-optimizer (IC) iteration, with observable edits to their design, before documenting their project. Figure 5-7 shows detailed session time plots of Participants 01 and 03, who exhibited characteristics of the Complete Cycle. In these detailed session time plots, creation of a new variable is indicated by a circle, and a participant returning to sketching by picking up their writing utensil is shown by a triangle. The figure also shows when the designers defined the difference between solid and glass panels in their model (Sp) along with notable instances within the eye gaze fixations.

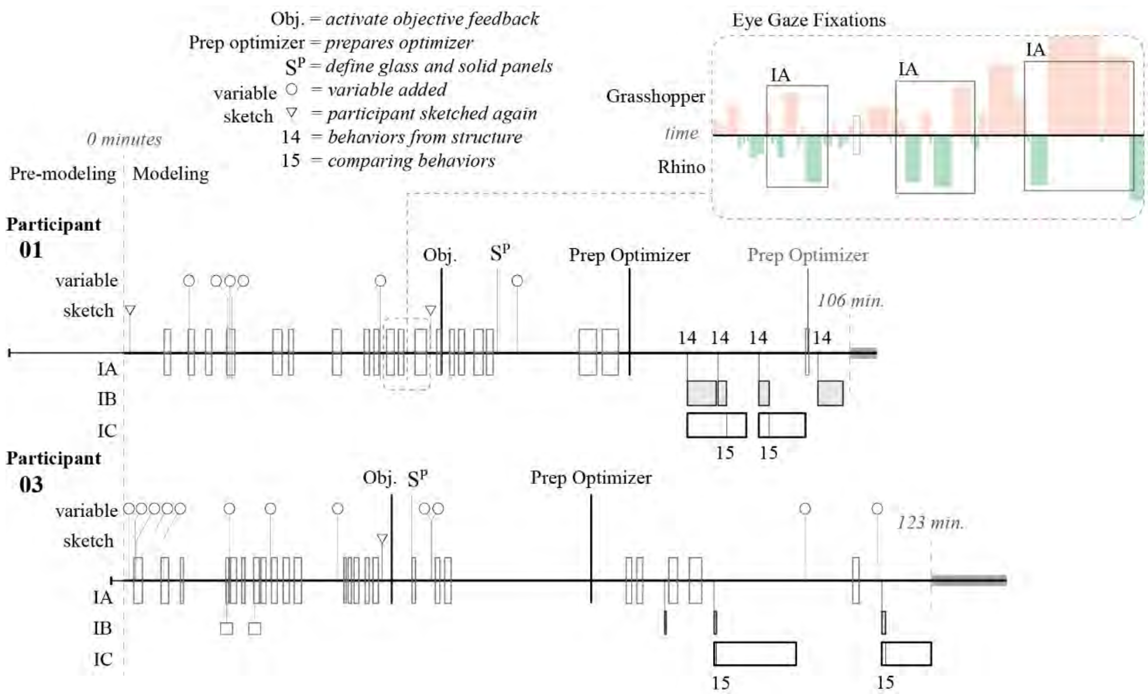


Figure **5-7**. Complete optimization cycle sessions with detailed time plots from Participants 01 and 03.

The enlarged portion of the Eye Gaze Fixation plot for Participant 01 shows three examples of IA iteration. The designer looked back and forth between the model space and parametric space for at least 4-12 second clusters, suggesting a loop of design edits, which was confirmed by researcher observation. As the sessions progress and the designers focus more on preparing for the optimization process, the occurrences of IA loops become less frequent. However, each designer also completed an IA loop between optimization runs, suggesting that an informed change was made to the design before running the final optimization loop. Several smaller differences are apparent, however. Participant 01 returned to sketching after placing a component and before developing their model, while Participant 03 immediately started to create variables. Also, as indicated by the early square notations in the IB zone, Participant 03 used a direct form-finding tool to achieve an optimized structural shape first rather than use “structure” as an objective in a parametric optimization run. This is a distinct form of optimization based on setting optimality criteria and seeking those criteria directly, but it is only possible in a parametric environment designed specifically for this purpose. It was thus coded for summary statistics as an optimization loop but represented differently from an IB loop.

### 5.4.2 Coarse Optimization Cycle

Figure 5-8 shows the detailed time plots two designers who exhibited a “Coarse Optimization Cycle.” It includes Participants 05 and 06, who completed IC loops but did not use optimization strategies thoroughly and thus presented subtle differences in their sessions. The IC loops of these sessions are very brief compared to Participants 01 and 03. Although the brevity of an IB loop will depend on the robustness of the chosen tool and the simplicity of a design, time spent considering the optimized options (process 15) can reflect the sophistication of the optimization run or the intent of the designer. These two participants ran several IB loops in a short time because the design options were not as diverse as they envisioned, but they did not know how to manipulate the variables to produce optimization results that aligned with their vision. Participant 05 did not engage in optimization events until late in their session and realized the structure of their model’s code was not compatible with the requirements of objective generators. The participant rebuilt part of the model and lost some of the qualities from their original design. The detail from Participant 05’s time plot in Figure 5-8 shows their focus on Grasshopper space as they manipulated code.

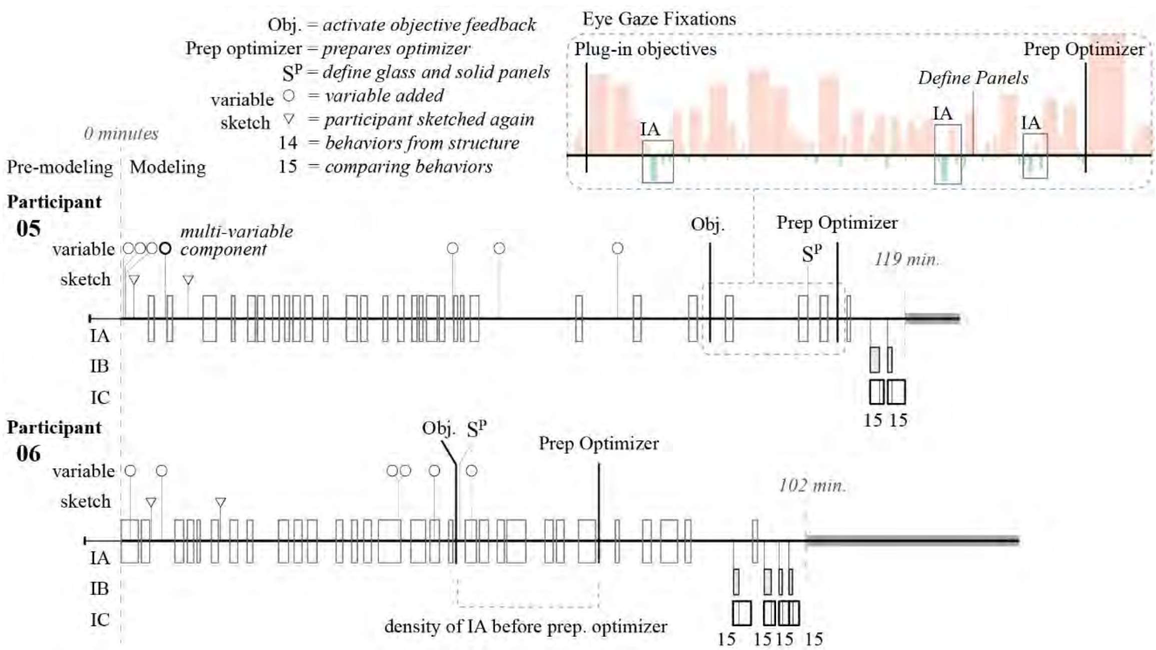


Figure **5-8**. Coarse optimization cycle sessions with detailed time plots from Participants 05 and 06.

While other sessions show sparse IA iterations as participants adjusted code, Participant 06's time plot shows a density of IA iterations before preparing the optimization tool. This behavior suggests that, for Participant 06 to correctly activate the objective generators, they had to change their design and repeatedly view the results in the model space. The absence of this behavior in the other sessions suggests that this designer's solution developed in response to the guided requirements of the study, not exclusively by their own vision for the project. This dependency on prompted Grasshopper coding may reflect less experience with parametric and optimization design techniques. Although this participant could wield optimization tools, issues with self-driven design performance may arise if they were to employ optimization techniques in future, professional projects where design efficacy and efficiency are imperative.

### 5.4.3 Partial Optimization Cycle

Figure 5-9 shows the plots for Participants 02 and 04, who did not complete an IC loop during the study. This characteristic is considered a "Partial Optimization Cycle." Although most of the designers responded to the optimization tool's feedback, Participant 04 started writing their final design statement before completing their first optimization run. This suggests that either the variables affecting the participant's design were not dependent on the optimization feedback, or that the participant did not consider their optimization routine to have possible benefits for informing a final design decision. However, a lack of IC iterations does not always mean that optimization techniques were not used to improve the design. In Participant 02's first two optimization runs, they watched the tool generate a range of possible designs while it ran. After briefly seeing that the possible solutions were not as varied as they hoped, the designer stopped the optimizer's automated process and edited their design variables to create more variations of possible solutions. This was an informed action as part of a process 13 (considering the physical structure of the design), but not a process 15, and therefore not an IC iteration. Nevertheless, the optimization tool was integrated into the participant's design strategy.

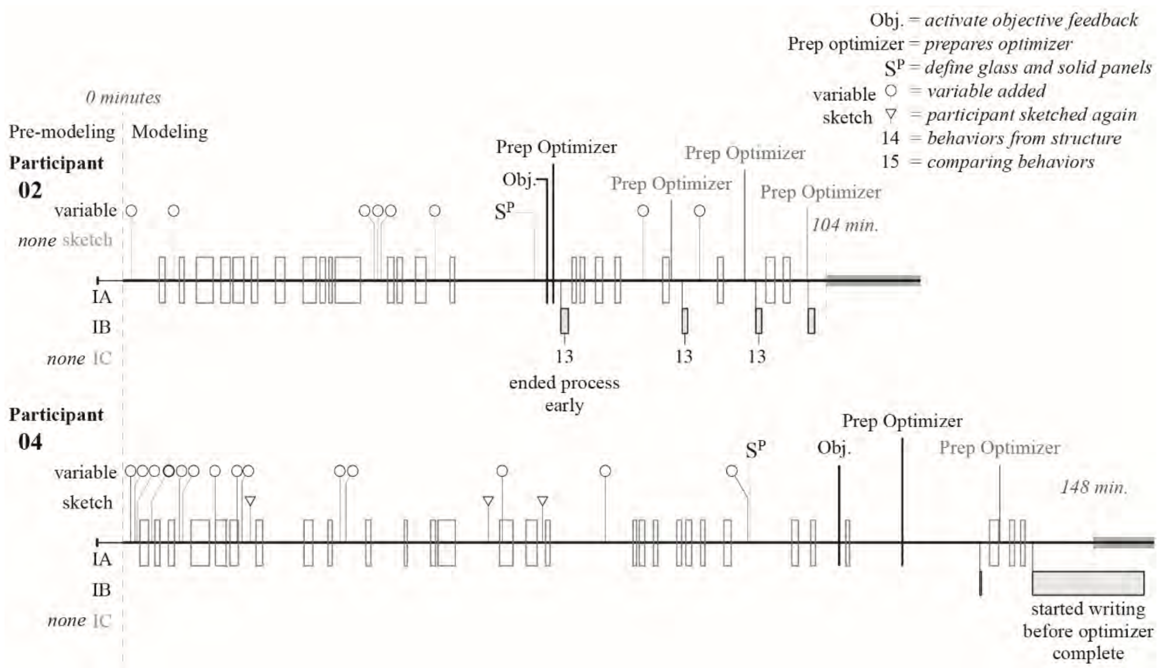


Figure **5-9**. Partial optimization cycle sessions with detailed time plots from Participants 02 and 04.

### 5.4.4 Optimization Characteristics

Figure 5-10 summarizes the optimization characteristics for six representative sessions that were analyzed in more detail. The figure shows what percentage of the session had transpired before the participant engaged with the objectives' components and when they started to prepare the optimization tool. The participants began using the objective components at between 43-75% of the timeline, suggesting a transition from developing the structure of the model to considering the behaviors of their model. After plugging their designs into the objective generators, participants began to optimize at different times as well. While Participant 03 started to optimize as early as halfway through the session, Participant 05 did not start optimizing until near the end of their session. Figure 5-10 also indicates which of the two objectives the participants focused on in their optimization sequences. Finally, it states how many IA, IB, and IC iterations that the participants performed and how many variables were used in their final IB run. The parenthetical number (5) for Participant 03's IB loops shows the number of direct form-finding runs employed.

| Participant | 01 | 02 | 03 | 04 | 05 | 06 |
|---|---|---|---|---|---|---|
| Session Timeline<br>*obj.=activate objectives*<br>*opt.=prep optimizer* | obj. 43% opt. 70% | obj. 60% opt. 61% | obj. 33% opt. 58% | obj. 69% opt. 76% | obj. 75% opt. 91% | obj. 50% opt. 71% |
| Objectives | daylight<br>energy<br>structure | daylight<br>energy<br>structure | daylight<br>energy<br>structure | daylight<br>energy<br>structure | daylight<br>energy<br>structure | daylight<br>energy<br>structure |
| IA | 20 | 23 | 24 | 29 | 29 | 30 |
| IB | 4 | 4 | 3 (5) | 2 | 2 | 4 |
| IC | 2 | 0 | 2 | 0 | 2 | 4 |
| Final variables | 6 | 3 | 6 | 5 | 16 | 7 |

Figure **5-10**. Summary of characteristics from the optimization portion of each session.

The number of variables used in the final optimization output varies by participant. Participant 05 had the most variables, which may explain why they spent so much time generating code before beginning to optimize, but Participant 04 had a similar delay with fewer variables. Although all designers created variables (parametric sliders) early in their design, only Participants 01 and 06 used all of these sliders in their optimization process. In some cases, variables were only used by the designer to consider design variations outside of the optimization framework.

## 5.5 Discussion

To summarize, several design patterns emerge from the results. Three iterative loops were identified from applying the situated FBS ontology to differentiate iterations from the designer, the optimization tool, and from the designer and optimization tool together. These loops can show when a designer relies on their own design knowledge to make decisions or when they use optimization feedback to inform their design. The occurrence of these loops defined the three categories of design strategies based on their presence, timing, and repetition.

This research shows that the graduate student designers use optimization with varying degrees of intent. While some used optimization feedback to understand the extents of their parametric model (like Participant 02) or inform changes to their design (like Participant 01 and 03), others did not fully integrate optimization into their design strategies. This behavior is evident in sessions that did not make edits between optimization IB iterations (like Participant 05) or did not complete an IC iteration (like Participant 04). Participant 04 showed a partial use of optimization tools, and their behaviors suggest that their vision for their design was not responsive to optimization feedback, since their documentation was started before the optimizer completed its assessment. Not using optimization feedback in this case may reflect design fatigue within the context of the study, as their session lasted longer than the other participants'. From observing their parametric model, though, their optimization variables controlled only subtle changes to the model, suggesting that optimization as an influencer in design was not part of their strategy. Only partial or no use of optimization feedback in student designers may indicate a lack of experience or comfort with optimization tools, or it may simply show a preference for other design approaches.

Although the participants tended to create many variables (or parametric sliders) early in their design session, not all variables were included in the optimizer's process. Many of the variables were used to explore design options manually rather than as part of their performance-driven investigation, but they could also have been used to set a parameter or constraint that did not change during optimization. While previous research has discerned schemes for processing parametric design behavior [20], [71] and identified an iterative loop between design decisions and optimization [41], the findings from this experiment confirm the presence of these loops while developing a parametric script during design. This paper thus adds to existing knowledge by showing how early and frequently students modify their model structure in response to an optimization cycle.

### 5.5.1 Implications for Design Pedagogy

In categorizing the sessions by optimization behaviors, we establish an initial method to identify the characteristics of graduate student designers, which can inform future curricular development and even student assessment if measured directly. Students with experience using optimization tools do not always fully incorporate them into their decision-making process in a way that leverages optimization's strengths. If the goal of having optimization in the curriculum is to empower students to include such automated or interactive optimization runs to improve design outcomes, then additional emphasis must be placed on contextualizing optimization for design. This could include formal teaching of strategies for variable selection and parametric problem definition, visual interpretation of results, and how to use optimization iteratively to arrive at a satisfying result. Particular topics of emphasis may differ across the disciplines in the study, as the goals of optimization in an architecture studio or graduate engineering course are likely different.

In addition, when considering how much of the design session the participants spent optimizing, the results suggest that incorporating objective feedback earlier in the design session aligns with more IC designer-optimizer iterations. The designers who started preparing for the objective feedback sooner in the sessions ran more optimization iterations. While getting to the optimization process sooner provides more opportunities for design improvement, it does not ensure quality of design expression. However, in optimization education, emphasizing the early and integrated use of optimization for student designers can at least prompt more engagement with the approach.

Finally, this study noted that when given the choice, most participants selected either the default evolutionary solver native to the software itself or a multi-objective optimization tool that uses an evolutionary process to generate approximations of the Pareto front for further consideration. If instructors seek to encourage students to use faster gradient-based algorithms, interactive tools, or other methods beyond evolutionary algorithms, more emphasis on these alternative methods is likely needed. These tool preferences may also have occurred for practical reasons, such as ease of access or use, rather than because students thought they would achieve the best results, but this would have to be determined through future study.

### 5.5.2 Limitations

As with any study, there are some limitations to the findings. Although there were only ten participants, the data generated from this project is insightfully rich in ways that have not been presented in the AEC design literature before by using deep multimethod qualitative and time-resolved observational research methods. Our data set from ten participants represents approximately thirty hours of in situ observational data employing multiple strands of time-resolved data, offering a unique depth of insight useful to design theorists and educators. Further, the goal of the study was to identify designerly behavior during optimization in intermediate-level designers to promote theory-informed transferability of the research findings, not to understand how predictively generalizable these patterns occur across larger populations. We leave this to future work. The advantages and affordances of using deep qualitative methods will always be balanced with a pragmatic tradeoff of sample size, as has been well-established in the qualitative research methods literature. We meet the requirements of qualitative research methodologies by grounding our work in theory, establishing theoretical and pragmatic validity [72] through our use of and interpretation of results through FBS design theory, and are satisfied with our codebook in that we reached saturation such that no new themes emerged during analysis [73], [74].

In addition, this chapter does not present the disciplinary backgrounds of the studies' participants, which was discussed in section 2.2.1. Analysis and discussion of their disciplinary backgrounds are presented in the paper "Optimization strategies of architecture and engineering graduate students: responding to data during design" included in the proceedings of the 2023 CAAD Futures 2023 conference. The details of the participants' education as an architect or engineer was excluded from this dissertation because these distinctions were less influential on differences of design behavior when comparing students to practitioners in optimization.

Other limitations to this study include that the design task focuses on a conceptual design challenge, which does not capture all possible strategies that may be used when developing a full project. However, optimization strategies are often used to explore solutions at early phases of design to investigate concepts of interest. Studying a design challenge with a narrow activity scope rather than a comprehensive design process creates many advantages for data collection, but may also diminish its authenticity. In addition, since students were able to select their own tools, this study does not cover behaviors across the full range of optimization possibilities, including more emerging interactive optimization strategies. Finally, this study does not assess design quality directly, so it assumes that full incorporation of optimization into design simply gives the best future opportunity for high-quality designs. Several of these limitations are left for future work.

## 5.6 Conclusion

This paper presented the findings from a study which considered the designerly behaviors of graduate student designers in architecture and architectural engineering when responding to a building design optimization task. The study used eye-tracking and screen recording methods to record data and coded the designerly behaviors following the situated FBS framework. Three types of design iteration loops were used to characterize partial, coarse, and complete optimization cycles by participants. These findings from this study, while of interest to education and design cognition researchers in advancing foundational theory, also offer significant opportunities to modify and augment graduate-level design curricula in architectural engineering and related fields. As the categories of cycles suggest, while the students understood how to run the optimization tools, not all were prepared to use the performance feedback in their own designs. While graduate-level education may show students how to use the optimization tools, students need to know how to integrate the tools in design projects as well. In much of architectural engineering education curricula, digital design tools are often taught secondary to design concepts, which is appropriate for certain applications, but incorporating digital tools in graduate-level education can better prepare student designers to use the tools effectively rather than as an afterthought.

In addition, the use of observational methods in an authentic design challenge offers insight on common issues, obstacles, or ineffective design strategies often employed that may be missed in typical “expert vs novice” studies. The impact of this work lies in the preparation of a future workforce that is computationally agile in their future careers, helping them use simulation feedback to design buildings that are more energy-efficient, low carbon, safe, and durable.

In future work, it is necessary to consider how the categories of optimization behavior proposed here relate to other variables in the optimization design process, as well as to the quality of design outcomes. For example, future behavioral studies that evaluate the quality of designs produced can indicate which optimization-based processes are more effective and should thus be taught to student designers. The methods for observing optimization behavior presented in this paper provide a scheme by which to continue to examine designers’ optimization strategies. They can be adjusted to accommodate the discovery of new techniques and tools using quantitative methods. Nevertheless, this study observed several clear patterns in design optimization behavior, showing that earlier and iterative incorporation of optimization runs by graduate student designers can lead to more critical engagement with the feedback they provide.

*Data Availability Statement*: All data, models, or code generated or used during the study are proprietary or confidential in nature and may only be provided with restrictions with accommodation from the International Review Board (eye-tracking files, screen recordings, researcher notes).

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**References**

[1] J. Felkner, E. Chatzi, and T. Kotnik, “Interactive particle swarm optimization for the architectural design of truss structures,” in 2013 IEEE Symposium on Computational Intelligence for Engineering Solutions (CIES), J. Felkner, E. Chatzi, and T. Kotnick, Eds., Singapore: IEEE, Apr. 2013, pp. 15–22. Doi: 10.1109/CIES.2013.6611723.

[2] E. Touloupaki and T. Theodosiou, “Optimization of building form to minimize energy consumption through parametric modelling,” Procedia Environ Sci, vol. 38, pp. 509–514, 2017, doi: 10.1016/j.proenv.2017.03.114.

[3] C. T. Mueller, “Computational exploration of the structural design space,” Dissertation, Massachusetts Institute of Technology, Boston, 2014.

[4] P. Heiselberg, H. Brohus, A. Hesselholt, H. Rasmussen, E. Seinre, and S. Thomas, “Application of sensitivity analysis in design of sustainable buildings,” Renew Energy, vol. 34, no. 9, pp. 2030–2036, Sep. 2009, doi: 10.1016/j.renene.2009.02.016.

[5] A.-T. Nguyen, S. Reiter, and P. Rigo, “A review on simulation-based optimization methods applied to building performance analysis,” Appl Energy, vol. 113, pp. 1043–1058, Jan. 2014, doi: 10.1016/j.apenergy.2013.08.061.

[6] L. Wang, H. Wong Nyuk, and S. Li, “Facade design optimization for naturally ventilated residential buildings in Singapore,” Energy Build, vol. 39, no. 8, pp. 954–961, Aug. 2007, doi: 10.1016/j.enbuild.2006.10.011.

[7] S. Attia, J. L. M. Hensen, L. Beltrán, and A. De Herde, “Selection criteria for building performance simulation tools: contrasting architects’ and engineers’ needs,” J Build Perform Simul, vol. 5, no. 3, pp. 155–169, May 2012, doi: 10.1080/19401493.2010.549573.

[8] J. Nocedal and S. J. Wright, “Chapter 1 Introduction,” in Numerical Optimization, Second.2006, pp. 1–9.

[9] R. T. Marler and J. S. Arora, “Survey of multi-objective optimization methods for engineering,” Structural and Multidisciplinary Optimization, vol. 26, no. 6, pp. 369–395, Apr. 2004, doi: 10.1007/s00158-003-0368-6.

[10] C. T. Mueller and J. A. Ochsendorf, “Combining structural performance and designer preferences in evolutionary design space exploration,” Autom Constr, vol. 52, pp. 70–82, Apr. 2015, doi: 10.1016/j.autcon.2015.02.011.

[11] M. Turrin, P. von Buelow, and R. Stouffs, “Design explorations of performance driven geometry in architectural design using parametric modeling and genetic algorithms,” Advanced Engineering Informatics, vol. 25, no. 4, pp. 656–675, Oct. 2011, doi: 10.1016/j.aei.2011.07.009.

[12] E. Touloupaki and T. Theodosiou, “Performance Simulation Integrated in Parametric 3D Modeling as a Method for Early Stage Design Optimization—A Review,” Energies (Basel), vol. 10, no. 5, p. 637, May 2017, doi: 10.3390/en10050637.

[13] J. S. Gero and U. Kannengiesser, “The situated function–behaviour–structure framework,” Des Stud, vol. 25, no. 4, pp. 373–391, Jul. 2004, doi: 10.1016/j.destud.2003.10.010.

[14] N. Cross, Design Thinking: Understanding how Designers Think and Work. Oxford: Berg, 2011.

[15] N. Cross and N. Roozenburg, "Modelling the design process in engineering and in architecture," Journal of Engineering Design, vol. 3, no. 4, pp. 325–337, Jan. 1992, doi: 10.1080/09544829208914765.

[16] B. Lawson, How Designers Think, 4th edition. Norfolk, UK: Routledge, 2006. doi: 10.4324/9780080454979.

[17] P. Rowe, Design Thinking. Cambridge, MA: MIT Press, 1987.

[18] J. Haymaker et al., "Design space construction: A framework to support collaborative, parametric decision making," Journal of Information Technology in Construction, vol. 23, pp. 157–178, 2018.

[19] M. Burry, "Between intuition and process: parametric design and rapid prototyping," in Architecture in the digital age, B. Kolarevic, Ed., 1st Edition.London: Taylor & Francis, 2003, pp. 147–162.

[20] R. Oxman, "Thinking difference: Theories and models of parametric design thinking," Des Stud, vol. 52, pp. 4–39, Sep. 2017, doi: 10.1016/j.destud.2017.06.001.

[21] A. Stals, S. Jancart, and C. Elsen, "Parametric modeling tools in small architectural offices: Towards an adapted design process model," Des Stud, vol. 72, p. 100978, Jan. 2021, doi: 10.1016/j.destud.2020.100978.

[22] J. Tschetwertak, S. Schneider, A. Hollberg, D. Donath, and J. Ruth, "A Matter of Sequence," 2017, pp. 100–120. doi: 10.1007/978-981-10-5197-5_6.

[23] I. Caetano, L. Santos, and A. Leitão, "Computational design in architecture: Defining parametric, generative, and algorithmic design," Frontiers of Architectural Research, vol. 9, no. 2, pp. 287–300, Jun. 2020, doi: 10.1016/j.foar.2019.12.008.

[24] R. Yu and J. Gero, "An empirical foundation for design patterns in parametric design," in Association for Computer-Aided Architectural Design Research in Asia., Hong Kong, 2015, pp. 551–560.

[25] J. Harding, S. Joyce, P. Shepherd, and C. Williams, “Thinking topologically at early stage parametric design,” in Advances in Architectural Geometry, Paris, 2012.

[26] E. Kalkan, F. Y. Okur, and A. C. Altunışık, “Applications and usability of parametric modeling,” Journal of Construction Engineering, Management & Innovation, vol. 1, no. 3, pp. 139–146, Oct. 2018, doi: 10.31462/jcemi.2018.03139146.

[27] N. A. Megahed, “Digital Realm: Parametric-enabled Paradigm in Architectural Design Process,” International Journal of Architecture, Engineering and Construction, vol. 4, no. 3, pp. 174–183, Sep. 2015, doi: 10.7492/IJAEC.2015.018.

[28] T. Wortmann and B. Tunçer, “Differentiating parametric design: Digital workflows in contemporary architecture and construction,” Des Stud, vol. 52, pp. 173–197, Sep. 2017, doi: 10.1016/j.destud.2017.05.004.

[29] J. S. Gero, “Design prototypes: a knowledge representation schema for design,” AI Mag, vol. 11, no. 4, pp. 26–36, 1990, doi: 10.1609/aimag.v11i4.854.

[30] T. J. Howard, S. J. Culley, and E. Dekoninck, “Describing the creative design process by the integration of engineering design and cognitive psychology literature,” Des Stud, vol. 29, no. 2, pp. 160–180, Mar. 2008, doi: 10.1016/j.destud.2008.01.001.

[31] P. Kruchten, “Casting Software Design in the Function-Behavior-Structure Framework,” IEEE Softw, vol. 22, no. 2, pp. 52–58, Mar. 2005, doi: 10.1109/MS.2005.33.

[32] M. Yan, “Representing design knowledge as a network of function, behaviour and structure,” Des Stud, vol. 14, no. 3, pp. 314–329, Jul. 1993, doi: 10.1016/0142-694X(93)80027-A.

[33] G. Cascini, G. Fantoni, and F. Montagna, “Situating needs and requirements in the FBS framework,” Des Stud, vol. 34, no. 5, pp. 636–662, Sep. 2013, doi: 10.1016/j.destud.2012.12.001.

[34] K. Dorst and P. E. Vermaas, “John Gero’s Function-Behaviour-Structure model of designing: a critical analysis,” Res Eng Des, vol. 16, no. 1–2, pp. 17–26, Nov. 2005, doi: 10.1007/s00163-005-0058-z.

[35] P. Galle, “The ontology of Gero’s FBS model of designing,” Des Stud, vol. 30, no. 4, pp. 321–339, Jul. 2009, doi: 10.1016/j.destud.2009.02.002.

[36] C.-C. Gu, J. Hu, Y.-H. Peng, and S. Li, “FCBS model for functional knowledge representation in conceptual design,” Journal of Engineering Design, vol. 23, no. 8, pp. 577–596, Aug. 2012, doi: 10.1080/09544828.2011.629318.

[37] M. Uflacker and A. Zeier, “Extending the Situated Function-Behaviour-Structure Framework for User-Centered Software Design,” in Design Computing and Cognition ’08, Dordrecht: Springer Netherlands, pp. 241–259. doi: 10.1007/978-1-4020-8728-8_13.

[38] R. Yu, J. Gero, and N. Gu, “Architects’ cognitive behaviour in parametric design,” International Journal of Architectural Computing, vol. 13, no. 1, pp. 83–101, Mar. 2015, doi: 10.1260/1478-0771.13.1.83.

[39] J. Lee, N. Gu, and A. P. Williams, “Parametric Design Strategies for the Generation of Creative Designs,” International Journal of Architectural Computing, vol. 12, no. 3, pp. 263–282, Sep. 2014, doi: 10.1260/1478-0771.12.3.263.

[40] N. C. Brown and C. T. Mueller, “Design for structural and energy performance of long span buildings using geometric multi-objective optimization,” Energy Build, vol. 127, pp. 748–761, Sep. 2016, doi: 10.1016/j.enbuild.2016.05.090.

[41] P. Geyer and K. Beucke, “An integrative approach for using multidisciplinary design optimization in AEC,” in the International Conference on Computing in Civil and Building Engineering, W. Tizani, Ed., 2010.

[42] N. C. Brown, V. Jusiega, and C. T. Mueller, “Implementing data-driven parametric building design with a flexible toolbox,” Autom Constr, vol. 118, p. 103252, Oct. 2020, doi: 10.1016/j.autcon.2020.103252.

[43] D. J. Gerber and S.-H. E. Lin, “Designing in complexity: Simulation, integration, and multidisciplinary design optimization for architecture,” Simulation, vol. 90, no. 8, pp. 936–959, Aug. 2014, doi: 10.1177/0037549713482027.

[44] C. Stones and T. Cassidy, “Seeing and discovering: how do student designers reinterpret sketches and digital marks during graphic design ideation?,” Des Stud, vol. 31, no. 5, pp. 439–460, Sep. 2010, doi: 10.1016/j.destud.2010.05.003.

[45] J. B. Kollat and P. Reed, “A framework for Visually Interactive Decision-making and Design using Evolutionary Multi-objective Optimization (VIDEO),” Environmental Modelling & Software, vol. 22, no. 12, pp. 1691–1704, Dec. 2007, doi: 10.1016/j.envsoft.2007.02.001.

[46] T. W. Simpson and J. R. R. A. Martins, “Multidisciplinary Design Optimization for Complex Engineered Systems: Report From a National Science Foundation Workshop,” Journal of Mechanical Design, vol. 133, no. 10, Oct. 2011, doi: 10.1115/1.4004465.

[47] D. Yang, Y. Sun, M. Turrin, P. von Buelow, and J. Paul, “Multi-objective and multidisciplinary design optimization of a large sports building envelopes: a case study,” in International Association of Shell and Spatial Structures 2015 Amsterdam Symposium: Future Visions - Computational Design, Amsterdam, 2015, pp. 1–14.

[48] A. D. Radford and J. S. Gero, “On optimization in computer aided architectural design,” Build Environ, vol. 15, no. 2, pp. 73–80, Jan. 1980, doi: 10.1016/0360-1323(80)90011-6.

[49] M. A. Schnabel, “Learning Parametric Designing,” in Industrial Engineering, IGI Global, 2013, pp. 197–210. doi: 10.4018/978-1-4666-1945-6.ch013.

[50] S. C. Chase, “Generative design tools for novice designers: Issues for selection,” Autom Constr, vol. 14, no. 6, pp. 689–698, Dec. 2005, doi: 10.1016/j.autcon.2004.12.004.

[51] N. Cross, H. Christiaans, and K. Dorst, “Design Expertise Amongst Student Designers,” Journal of Art & Design Education, vol. 13, no. 1, pp. 39–56, Jun. 1994, doi: 10.1111/j.1476-8070.1994.tb00356.x.

[52] N. C. Brown and S. Bunt, "Optimization tools as a platform for latent qualitative design education of technical designers," in National Conference on Beginning Design Students, S. Burns and Kristin Barry, Eds., 2022.

[53] C. J. de Oliveira, L. O. Steffen, C. A. de M. Vasconcellos, and P. F. Sanchez, "Structural topology optimization as a teaching tool in the architecture," Revista de Ensino de Engenharia, vol. 37, no. 3, 2018, doi: 10.5935/2236-0158.20180039.

[54] A. Pasternak and K. Kwiecinski, "High-rise Building Optimization - A Design Studio Curriculum," 2015, pp. 305–314. doi: 10.52842/conf.ecaade.2015.1.305.

[55] N. C. Brown, "Design performance and designer preference in an interactive, data-driven conceptual building design scenario," Des Stud, vol. 68, pp. 1–33, May 2020, doi: 10.1016/j.destud.2020.01.001.

[56] N. C. Brown and C. T. Mueller, "The effect of performance feedback and optimization on the conceptual design process," in International Association of Spatial Structures Annual Symposium, Tokyo, Sep. 2016. [Online]. Available: https://www.researchgate.net/publication/316107726

[57] E. Mark, "Optimizing solar insolation in transformable fabric architecture: A parametric search design process," Autom Constr, vol. 22, pp. 2–11, Mar. 2012, doi: 10.1016/j.autcon.2011.11.001.

[58] C. J. Atman, R. S. Adams, M. E. Cardella, J. Turns, S. Mosborg, and J. Saleem, "Engineering Design Processes: A Comparison of Students and Expert Practitioners," Journal of Engineering Education, vol. 96, no. 4, pp. 359–379, Oct. 2007, doi: 10.1002/j.2168-9830.2007.tb00945.x.

[59] M. Deininger, S. R. Daly, K. H. Sienko, and J. C. Lee, "Novice designers' use of prototypes in engineering design," Des Stud, vol. 51, pp. 25–65, Jul. 2017, doi: 10.1016/j.destud.2017.04.002.

[60] D. Rutten, "Galapagos: On the Logic and Limitations of Generic Solvers," Architectural Design, vol. 83, no. 2, pp. 132–135, Mar. 2013, doi: 10.1002/ad.1568.

[61] R. A. Danhaive and C. T. Mueller, “Combining parametric modeling and interactive optimization for high-performance and creative structural design.,” in Proc., IASS Annual Symp, Madrid, Spain: International Association for Shell and Spatial Structures, 2015.

[62] Wallacei X, “www.wallacei.com.” Makki, M., 2018.

[63] N. C. Brown and C. T. Mueller, “Gradient-based guidance for controlling performance in early design exploration,” in Proc., IASS Annual Symp., Madrid, Spain: International Association for Shell and Spatial Structures, 2018.

[64] C. Preisinger and M. Heimrath, “Karamba—A toolkit for parametric structural design,” Structural Engineering International, vol. 24, no. 2, pp. 217–221, May 2014, doi: 10.2749/101686614X13830790993483.

[65] A. Zalewski, K. Borowa, and A. Ratkowski, “On Cognitive Biases in Architecture Decision Making,” in Software Architecture, 2017, pp. 123–137. doi: 10.1007/978-3-319-65831-5_9.

[66] EyeTracking, “EyeWorks Software.”

[67] P. Mehta, M. Malviya, C. McComb, G. Manogharan, and C. G. P. Berdanier, “Mining Design Heuristics for Additive Manufacturing Via Eye-Tracking Methods and Hidden Markov Modeling,” Journal of Mechanical Design, vol. 142, no. 12, Dec. 2020, doi: 10.1115/1.4048410.

[68] B. T. Carter and S. G. Luke, “Best practices in eye tracking research,” International Journal of Psychophysiology, vol. 155, pp. 49–62, Sep. 2020, doi: 10.1016/j.ijpsycho.2020.05.010.

[69] R. S. Hessels, C. Kemner, C. van den Boomen, and I. T. C. Hooge, “The area-of-interest problem in eyetracking research: A noise-robust solution for face and sparse stimuli,” Behav Res Methods, vol. 48, no. 4, pp. 1694–1712, Dec. 2016, doi: 10.3758/s13428-015-0676-y.

[70] A. Jbara and D. G. Feitelson, “How programmers read regular code: a controlled experiment using eye tracking,” Empir Softw Eng, vol. 22, no. 3, pp. 1440–1477, Jun. 2017, doi: 10.1007/s10664-016-9477-x.

[71] B. Y. Yu, T. Honda, M. Sharqawy, and M. Yang, "Human behavior and domain knowledge in parameter design of complex systems," Des Stud, vol. 45, pp. 242–267, Jul. 2016, doi: 10.1016/j.destud.2016.04.005.

[72] J. Walther et al., "Qualitative Research Quality: A Collaborative Inquiry Across Multiple Methodological Perspectives," Journal of Engineering Education, vol. 106, no. 3, pp. 398–430, Jul. 2017, doi: 10.1002/jee.20170.

[73] J. Saldana, The coding manual for qualitative researchers, 3rd ed. New York: SAGE, 2015.

[74] J. W. Creswell and J. D. Creswell, Research design: Qualitative, quantitative, and mixed methods approaches. New York: SAGE, 2017.

# Chapter 6

## Comparing Student and Practitioner Strategies and Cognition

This work will be submitted to a future journal publication as S. Bunt, C. G. P. Berdanier, N. C. Brown, "Comparing optimization strategies and cognitive processes of building design students and practitioners."

### Abstract

Optimization techniques are increasingly used in building design practice to support improved design solutions, however, designerly behaviors may be confounded by the cognitive influences of emerging optimization tools. Expertise is associated with reduced mental workload whereas absorbing new knowledge increases working memory. When developing and exploring a parametric model for optimization, designers iteratively receive information about their design's performance, and design cognition may be impacted by feedback loops in the design process. To understand the relationships between optimization strategies, cognitive loads, and experience with optimization tools, a study was conducted that tasked graduate students and practitioners to use optimization tools in response to a multi-objective, atrium roof design task. The design sessions were analyzed for significant design events and organized into optimization cycles of behavior. Eye-tracking methods were used to evaluate the designers' cognitive efforts, including ICA, fixation counts, and fixation durations. While the practitioners exhibited cognitive efforts aligning with their expected expertise, they also used a greater diversity of strategies compared to the students, who responded to optimization feedback less frequently. This paper reports variations in

their behavior and discusses what may influence designers to approach optimization tasks with different strategies.

Keywords: design process; optimization strategies; cognitive load, design expertise

## 6.1 Introduction

While addressing complex, multi-disciplinary objectives in design practice, architects and engineers are increasingly augmenting their processes with digital tools. For example, parametric design can support designers' decisions as they iterate a model towards improved performance with less manual effort. Within parametric environments, optimization tools rapidly search for solutions that meet a designer's quantitative requirements. When multiple objectives are present, which require prioritization to manage trade-offs, a designer can explore curated options provided by the tool rather than survey all possible solutions. Thus, while optimization algorithms can reduce aimless investigations by directing users to high-performance regions of the design space, they can also produce many design options with the potential for unconsidered new information.

This new information is likely to be processed differently by designers with varying levels of training, experience, and expertise. Novice and expert design approaches have been shown to be different in terms of cognitive effort [1], idea formulation [2], and the kinds of knowledge they use [3]. Such differences may be particularly acute in the context of optimization-based design tools. To achieve the potential benefits afforded by computational optimization, designers must know how to properly use the tools to their advantage. Emerging digital tools require new skills on top of traditional design training. Thus, students who are learning about building systems and how to properly design them at the same time they are learning how to appropriately use optimization might be overwhelmed by the new information. In contrast, practicing designers have already acquired design experience in their domain, and those experienced in optimization may be more comfortable in integrating optimization into their natural design approach in diverse ways.

The concept of cognitive load may be helpful in distinguishing students from practitioners, helping educators identify which gaps remain in their education. Research has established that increased cognitive load is correlated with the retention of new information [4] and task complexity can demand more working memory [5]. Working memory is also associated with increased cognitive load [6] and is responsible for processing new information into long-term, permanent knowledge [7], [8]. As a result, expertise often aligns with less cognitive load since an expert is not interpreting new information. Yet building design evokes novel solutions with each new project.

In addition, since emerging optimization tools prompt new strategies for design exploration, the processes and cognitive behaviors of expert designers may not align with expected characteristics from established research. Previously, novices have been known to use less efficient strategies and exert greater cognitive effort compared to experts [1]–[3], [9]. However, research specific to computational building design suggests that design expertise is ephemeral with the evolution of new tools, and that rapid design feedback leads designers to continually learn about their model [10]. While designers may use different approaches depending on their expertise, it is possible that they exert similar amounts of mental effort when performing optimization processes. As a result, workflow benefits from using optimization techniques to explore design options may be reduced if a designer’s efforts are restricted by increased cognitive load.

To better understand differences between student and practitioner design optimization strategies, with potential insights coming from both identified behaviors and measurements of cognitive load, a design study was conducted that asked students and practitioners to respond to a building design task with multi-objective goals. Participants were instructed to use optimization tools to seek improved design proposals. We follow Tan's [11] description of expertise based on experienced knowledge to identify optimization *practitioners*, who have applied optimization techniques to design projects for implementation. Conversely, we identify *students* as designers who have had exposure to optimization tools and techniques but have not yet applied optimization in practice. From each participants' design session, screen recordings, eye-tracking data, and interview feedback were collected. From this data, the optimization strategies were categorized based on completeness and uniformity following the established protocol for identifying optimization processes from chapter 5 [12].

In addition, eye-tracking tools collected pupil dilation and gaze data to measure mental workloads and evaluate the cognitive efforts exhibited by the designers using different strategies. Based on previous research, we expected differences in design cognition between the two groups, with the practitioners exhibiting less overall cognitive effort. However, there is not a standardized process for incorporating optimization techniques in design and we considered the possibility that session outcomes could vary by participant. This paper presents the range of strategies observed and discusses why complex design processes may elicit cognition results that are not explained by traditional metrics. Moreover, understanding distinctions in optimization processes between students and practitioners can influence how educators prepare designers to enter the profession to better address multi-objective design challenges.

## 6.2 Background

While cognitive load theory has established relationships between cognition and information [4], and researchers in design fields have used it to describe design behavior, less is known about cognitive effort in design optimization processes. Engineering design research has also considered cognitive load during prototyping design tasks with an emphasis on design outcomes [13],[14]. However, little research has focused on design cognition in architectural building optimization. Since building designers use optimization techniques in practice, their strategies and mental workload may affect their design performance.

### 6.2.1 Optimization in Building Design

Multi-objective optimization techniques are used in building design practice to explore otherwise difficult to compare design goals [15], [16]. Optimization tools can provide performance feedback about daylight [17], energy consumption [18], [19], and structural performance [21], and have been shown to improve design process [21]. Despite its usefulness, optimization processes in building design require sophisticated strategies to explore a design space and identify improved solutions.

While "design optimization" can refer to formal mathematical optimization [22], [23], or to the process of systematically improving the design performance of a current solution as might be used in building simulations [24], [25], recent research acknowledges the potential for design exploration in the process of optimization [26]–[28]. In applying optimization techniques in 3D building modeling spaces, designers may rely on both numeric and geometric feedback to iterate and improve a building's performance. For example, a designer might construct a model with variables and objectives, apply an optimization tool to find solutions that meet the goals of the design problem, and either select a design from the tool's output or edit the model in pursuit of other iterations. Exploration ends at the designer's discretion.

Due to the complexity of building design goals, with objectives spanning qualitative and quantitative dimensions, recognizing when to stop designing or to continue iterating requires elevated design knowledge from the designer. Previous researchers have recognized the challenges of navigating optimization tool feedback, proposing additional tools for interpreting information [29]. Additional studies have identified hinderances in using optimization tools, such as slow evaluation times with poor user interfaces [30] and a lack of established design processes [31]. With no standard for how to approach design optimization challenges, it is difficult to determine what strategies may be associated with greater optimization knowledge. Established distinctions between experts and novices may provide initial expectations of optimization techniques, but a designer's experience in optimization may be more useful to determine their design processes rather than years of experience in their profession.

### 6.2.2 Practice in Design Techniques

Previous research has shown that variation in amount of professional experience often result in different design processes [3], [9] with studies focusing on various aspects of design. Ahmed et al [2] observed that novice designers tended to use trial-and-error techniques while experienced designers were more systematic in design approaches. In comparing series of cognitive actions in design, Kavakli and Gero [1] found that novice designers followed more sequences of cognitive processes compared to experts, who had smaller variations in sequences and were more efficient in their cognitive actions. More specific to developing design spaces, Abdelmohsen and Do [32] found that novice architect designers performed prolonged processes to achieve the same goal as experts when responding to both sketching and parametric modeling tasks. However, in a study by Atman et al. [33] that focused on engineering design contexts, differences in expertise resulted in longer design sessions and an increase in design considerations for experts, but not necessarily increased design quality.

A recent paper by Tan [11] identified that existing models for expertise may not be best suited to describe expertise in all areas of design. Tan acknowledges that some existing, quantitative metrics for expertise, such as years of experience, may not capture the knowledge gained from performing a particular design task in practice. Tan also acknowledges that qualifying experience as a proxy for expertise may be subjective since it is abstract and prone to personal interpretation, but it nevertheless speaks to skills rather than numerical performance, which is not always measurable in design fields. In addition to experiential knowledge, Tan describes expertise as requiring adaptability, perceptiveness, and motivational support. In building design, many projects have their own unique contexts, challenging designers to adjust their design schemes, and new technologies and advances in techniques require designers to redefine their design paradigms. Such changes of design thinking are likely to affect our understanding of cognitive activity in design as well.

### 6.2.3 Cognition in Design Tasks

Since architectural building design requires visual and numeric decision-making, researchers have considered eye-tracking methods for data collection as a metric for cognitive load in design [34]. Many metrics are available in eye-tracking methods, such as fixation, saccades, gazes in areas of interest, and pupil dilation, and each can explain different behaviors and mental efforts related to the task being studied.

One metric of cognitive load is the Index of Cognitive Activity (ICA) which registers mental workload by relying on pupil dilation to indicate changes in brain activity, which has been associated with increased cognition [35], [36]. ICA is a patented metric [37] and can be calculated in the Workload Module software by EyeWorks [38]. Because raw ICA data can be difficult to interpret, Workload also produces a Scaled ICA metric for the left and right eyes. It detects and removes invalid pupil measurements and scales the pupil signal for each participant to a value between 0 and 1, with 1 being the maximum ICA that the participant experienced in the session. Research has found that for some tasks, an increase in ICA can reflect increases in cognitive effort [39], [40]. However, other research has questioned the accuracy of ICA in different contexts [41], [42] and found that it is not an effective measurement of cognitive load when participants are responding to two tasks simultaneously [43]. It is appropriate to consider additional streams of data when examining cognitive loads.

Another measurement of cognition is the number of fixations and duration of fixations during a task, which can indicate changes in cognitive processes [44]. However, the relationships of fixations to mental workload are also unclear, depending on the type of mental workload [45]. Some research found that longer fixations related to increased mental workload when interacting with artificial environments [46], while another found an inverse relationship between workload and fixation duration when playing an approachable video game [47]. An increase in the number of fixations may also indicate increased engagement with a task rather than the length of the fixation as a measure for mental workload. Nevertheless, fixations can provide an additional stream of information when evaluating cognitive behaviors.

Specific to design challenges, eye tracking data can also tell conflicting narratives. Research by Zimmerer et al. [48] has shown that eye parameters are more strongly influenced by tasks rather than by cognitive load. Zimmerer et al. attribute this result to design processes complexity which may cause different patterns in gaze behavior. Dissaux and Jancart [10] acknowledge that designers are iteratively learning from their tools when developing design ideas, and receiving information repetitively may disrupt previously established expectations of design thinking.

As the relationship between experience, cogitation, and design process in optimization strategies is unclear, the research presented in this paper considers the behaviors and mental efforts of students and practitioners when responding to a building optimization design task.

## 6.3 Methods

To compare characteristics between students and practitioners, we used a controlled design study that asked participants to develop a design for an atrium roof and we collected different streams of recorded data from their design sessions. Participants worked in a 3D, parametric modeling platform using optimization tools and reflected on their design decisions in a post-design session interview. In following appropriate protocol standards, this research is IRB approved and follows established eye-tracking and design behavior methods to examine the participants' design processes.

### 6.3.1 Participants

For this study, ten graduate students and nine design practitioners first completed an intake survey form which verified that they had enough experience within their field and with the study's design tools to respond to the design task. The students were from the Architecture or Architectural Engineering Department at a University in the North-eastern US and reported that they had at least 1 year of experience with Grasshopper and completed a course on design optimization. We considered their differences in disciplinary background in our paper "Optimization Strategies of Architecture and Engineering Graduate Students: Responding to Data During Design" [49], but this paper focuses on differences between groups of students and practitioners. All designers possessed educational experience in geometric and technical design, and we do not differentiate their educational background. For the practitioners, we followed a description for expertise defined by Tan [11] that states experiential knowledge can be used to qualify a designer's expertise. Similar definitions have been used in other research as well, in which experts have more contextual knowledge than a novice [33], [50]. We identified the practitioners' expertise by their use of optimization strategies in practice and confirmed that they had used optimization tools and techniques in a building design firm to develop at least 5 designs for a client. The practitioners also had at least 5 years of work experience in design firms. The practitioners were employed from 7 different firms, lived in 3 cities, and all had bachelor's and master's degrees in building design. Two of the practitioners were trained in Architectural Engineering, two in Civil Engineering, four in architecture, and one had a bachelor's degree in architecture and a master's in engineering. The purpose of this study is not to obtain generalizable results about the students and practitioners but rather identify different strategies and variations in cognitive load of designers while they developed and explored a design space for optimization.

After completing the survey, an initial interview was used to verify the practitioners' understanding of optimization in the context of building design in the study's tools. The interview also asked the practitioners about their use of optimization tactics in practice. Individual design sessions were then scheduled with each participant.

### 6.3.2 Design Sessions

The design sessions were conducted in either the researchers' office on the university's campus for the students or in the office spaces of design firms across the Northeastern and Midwest US for the practitioners. A member of the research team visited each practitioner to better facilitate their participation in the study. For each session, the designers worked on a computer provided by the researchers that hosted the study's tools and recorded the session data. Two screens were connected to the computer: one for the participant to work from and one for the researcher to watch the session. A table mounted eye tracker was used to collect data from the participant's eye movements and the designer's screens were recorded using EyeWorks Record (EyeTracking). Figure 6-1 shows the study's set up.

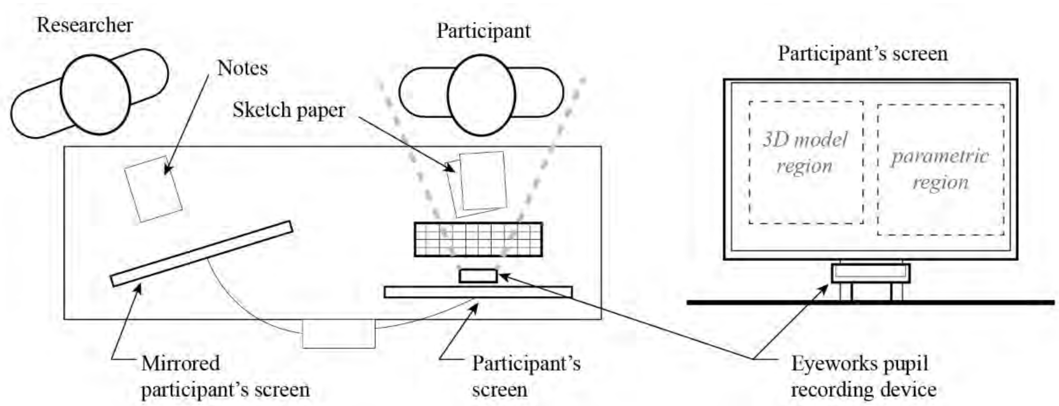



Figure **6-1**. Set up of the study's tools for the design sessions.

Before beginning the 3D modeling portion of the session, the participants were briefed on the design task by introductory videos which ensured that each participant received the same instruction. The participants were allowed to ask questions about the task before their eyes were calibrated to their position in front of the screen and data recording began.

### *6.3.2.1 Design Task*

The design task asked participants to develop a conceptual atrium roof for a fictional courtyard in the Southwestern US. The location was chosen since the environmental conditions of the region can readily be found online if the participant was not already familiar with the dry, sunny climate. Participants were instructed to consider the geometric and visual appearance of their design and select at least two of three quantitative objectives to optimize: daylight, energy, and/or structural elasticity. The study required the designers to work in Grasshopper, a parametric modeling tool hosted by the 3D modeling tool Rhinoceros, but participants were allowed to use any optimization plug-in tool for Grasshopper that they desired including Galapagos, Goat, Octopus, Wallacei [49], or DSE tools [52]. Participants were provided a starting Grasshopper script that included a model of the existing context for their design and calculations for instantaneous measurements of daylight, energy, and structural elasticity for noon on the summer solstice. Daylight and energy were calculated by angles of the design's surface to the sun and structural elasticity was calculated by Karama3D [53], a structural analysis program made for Grasshopper's parametric interface. Because this study focused on behaviors in optimization, we did not want the participants to run simulations. While running simulations can provide comprehensive information about a building's design, it can also add to the length of a design session, induce design fatigue, and may have deviated the designers' attention away from the purposes of this study.

Participants were asked to submit 3-5 screenshots of their design proposals and provide a brief design statement to the client, explaining their design intentions. The participants were not instructed on when to start writing their statement and were free to shift between design and writing. Notably, the participants were not explicitly instructed or required to use optimization tools to find an improved design solution.

#### *6.3.2.2 End of Session Interview*

After completing the design challenge, the eye recording was stopped, and the participants were prompted to reflect on their design sessions. They were asked to describe how they approached the design challenge and what they found to be the most challenging. Additionally, the researcher asked the participants about unique behaviors that were observed during the design sessions, such as starting a second design option.

### 6.3.3 Comparing Session Strategies and Cognition

Two primary streams of data are used to compare the behaviors of students to practitioners: evaluation of their design strategies by optimization cycles and cognitive load as measured by their eye-tracking data. Previous research has used both objective and subjective means to validate cognitive effort [42] as a single metric may not fully capture the complexity of a 3–4-hour design task.

#### *6.3.3.1 Design Session Evaluations*

The screen recordings of the design sessions were reviewed, and key design events related to the optimization process were identified. This allowed the design sessions to be compared for differences in strategies. Figure 6-2 illustrates the events on a sample timeline showing when participants engaged with the objective feedback, when they began to prepare the optimization tool, how often and how long they ran an optimization tool, how often and how long they reviewed the feedback from the tool, and when they wrote, if at all, while still developing their design.

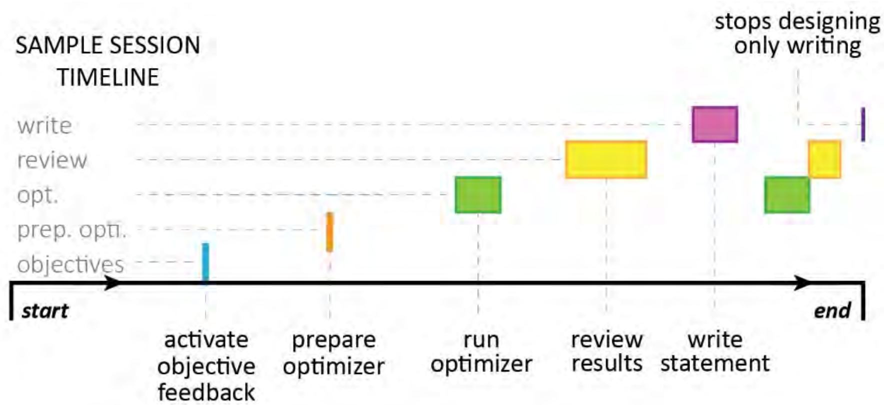



Figure **6-2**. An example time plot of the key events in the design sessions.

The sessions were also evaluated for their category of optimization cycles, following the method that was established in chapter 5 [12]. In chapter 5, optimization behaviors are described by three categories: (1) complete cycle in which a designer runs an optimization tool, reviews the results, and edits their design in response, (2) coarse cycle in which they run a tool and review results, but do not edit their design, and (3) partial cycle in which an optimization tool is run, but the numerical results are not reviewed. These cycles are identified by the presence of iteration loops between the designer and optimization tools as the designer gazes at the modeling space and parametric space. Instances of partial cycles were attributed to events in which designers use a tool to explore geometric limits to a design or do not understand how to best incorporate design performance feedback in their design. The work presented in this current paper uses these established cycles while including new data from the practitioners to compare the range of cycles exhibited by the two groups of participants.

#### *6.3.3.2 Eye-tracking Data*

To discuss differences in cognitive effort between the designers, we use three established metrics for cognition, which were collected by the eye-tracker: mean scaled ICA, fixation Count, and fixation duration.

The Mean scaled ICA for each participant was calculated by averaging the scaled ICA values between the left and the right eyes, which can indicate an increase in cognitive load [54]. Eye-works Workload Module calculates scaled ICA following a patented process [37] and normalizes the values for each participant on a 0.0 to 1.0 scale to produce scaled ICA values. Eye-works also recognizes when data was not received for a pupil and these items with their corresponding eye were removed from the data set. Some research reports that a higher ICA indicates an increase in cognitive load [39], however, other research found that ICA does not reflect cognitive load under all types of tasks [41]. As an additional measure for cognitive load in our study, other streams of eye-tracking data were considered.

The number of fixations and the duration of the fixations were examined across the two groups of students and practitioners. Fixations are measured when a participant looks at an area or region of interest and stops scanning across the screen. The design sessions lasted between 2-4.5 hours, so numerous fixations were collected for each participant. To better interpret the data across the sessions, the number of fixations every 5 minutes was used to determine fixation count. More screen fixations are sometimes associated with increased cognitive load as an indicator for processing new information, however, the duration of fixations can also indicate breaks in mental workflow. We also considered the duration of fixations for the participants as shorter durations should align with greater expertise in the parametric tool.

## 6.4 Results

The recordings of the design sessions, the researcher's notes, and the eye-tracking data were used to report categorical descriptions of design strategies and themes in the designers' cognition. The information is presented as a comparison between the students and practitioners, and, as an additional assessment of design behavior, the metrics for mental workload are arranged by optimization cycles.

### 6.4.1 Summaries and Categories of Design Sessions

From inspection of the session events, it is observed that the practitioners employed a wider variety of strategies in responding to the design task compared to the students. Figure 6-3 illustrates the key events on time plots of each session. While the students showed variations in the timing of their techniques, they mostly ran the optimization tool 1-4 times and reviewed the results before writing. The practitioners, however, used a wider range of different approaches. Participant P01 chose not to use the optimization tools to address the design task and instead relied on their own intuition and a sun path simulation to develop their design, resulting in an empty session plot. When asked during the post-session interview why they chose not to use optimization tools, despite being instructed to find a high performing building, they responded that the sun path simulation would solve concerns of shading while still producing a visually appealing design and that for this design, they would optimize aspects of structural design at a later phase of construction. P02 also did not use an optimization tool but reviewed the objective values and tried to minimize them manually. P04 ran the optimization tool 15 times (10 more times than any other participant) as they tried to resolve unexpected problems in their model, such the optimization tool proposing zero structural members to minimize structural elasticity. Unlike any other participant, P06 started preparing the optimization tool before plugging into the objective feedback, indicating their active awareness of optimization in their design procedure. Participants P03, P05, P06, and P07 started writing about their design while the optimizer was running, with P06 writing before even optimizing. One student, S04, started writing before they finished designing, but the student also did not review the numerical results from the optimization tool and treated optimization as an afterthought to their own design decisions.

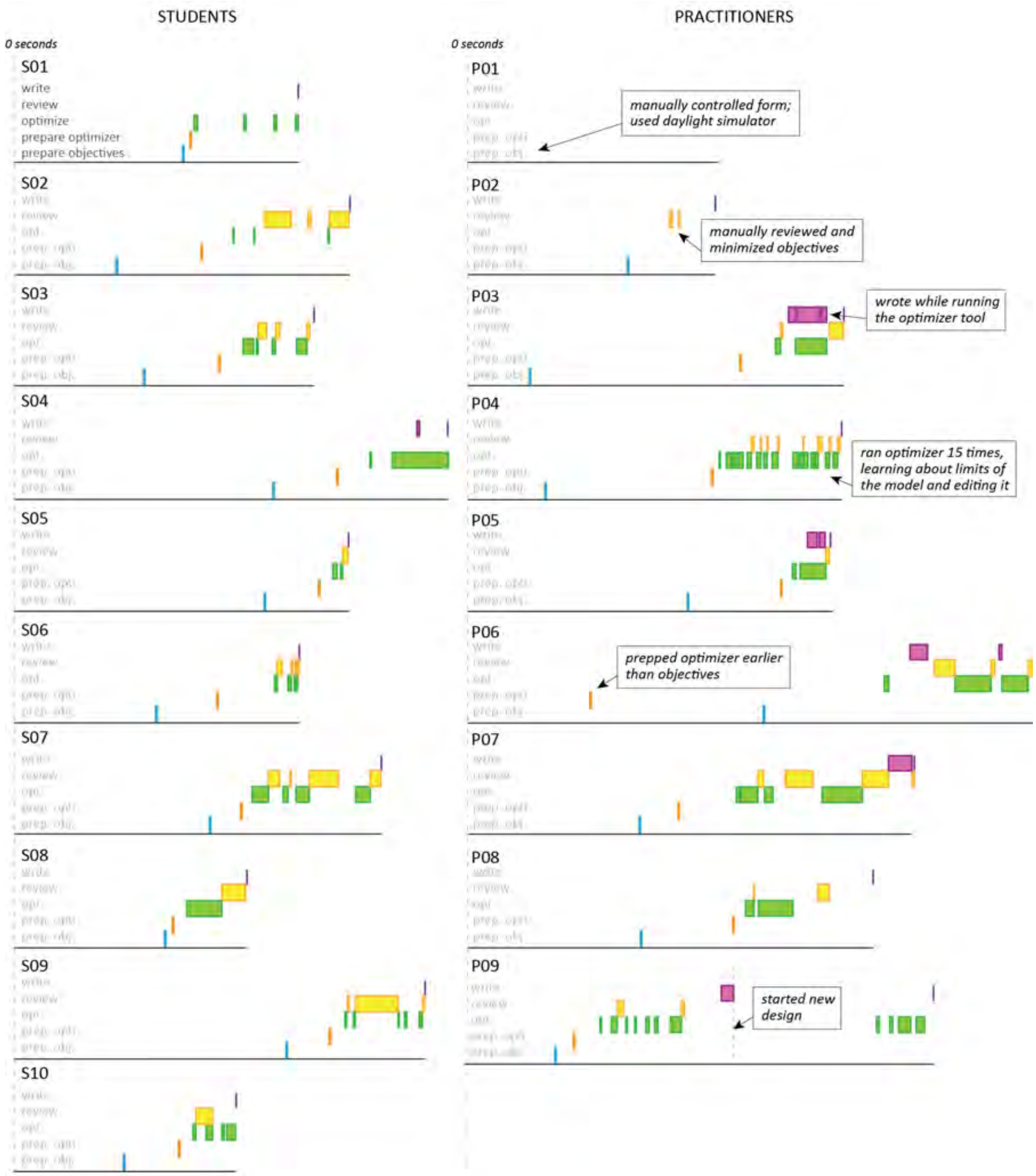



Figure **6-3**. The session plots of the design sessions.

In addition to the session plots, the optimization cycles of the participants are considered. Two of the practitioners chose not to run the optimization tool at all, which introduced the possibility of a fourth option in the categories of optimization cycles: independent. Six of the nine practitioners used a complete optimization session, indicating they incorporated feedback from the optimization tool in their design. Meanwhile, five of the ten students used a coarse cycle meaning they did not edit their design after reviewing the numerical results from the optimization tool. Figure 6-4 shows the number of students and practitioners who used the different optimization cycles.

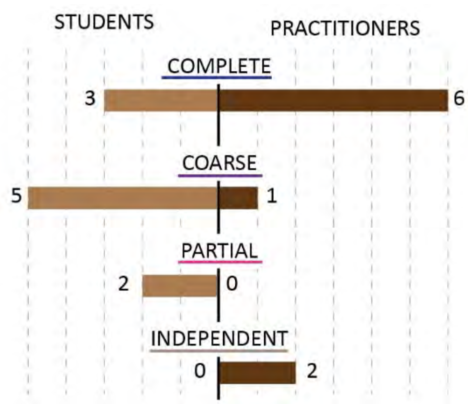
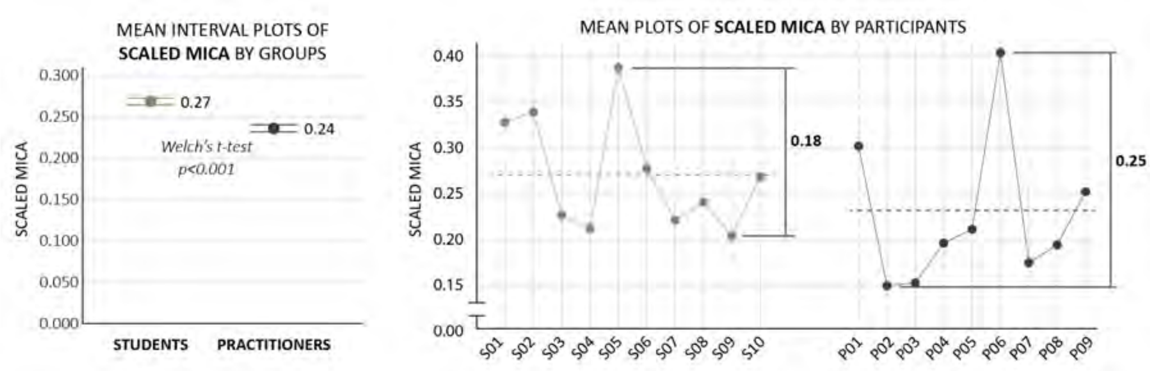



Figure **6-4**. The number of complete, coarse, and partial cycles of the students and practitioners.

### 6.4.2 Cognition Assessments

#### *6.4.2.1 Mean Scaled ICA*

The Index of Cognitive Activity was averaged for the left and right eyes for each participant and a Welch's t-test, which is an ANOVA test that assumes nonequal variance, was used to determine if the participants' Mean ICA (MICA) were statistically different. Because the data is skewed, a Levene test for equal variance was used to determine that the datasets do not have equal variance. From the Welch's t-test, the students' and practitioners' MICA was statistically different ($p<0.000$) at a $\alpha$=0.05 level of significance with the students having a higher MICA. Figure 6-5a shows a plot of their mean MICAs. According to Marshall [39] higher levels of ICA indicate increased overall cognitive load during the design sessions, but additional metrics should be used to understand the cognitive load of the participants. The means of each participant's Mean ICA were also considered and are shown in Figure 6-5b. While the practitioners as a group had a lower MICA, the practitioners also had a wider range of mean MICA compared to the students.

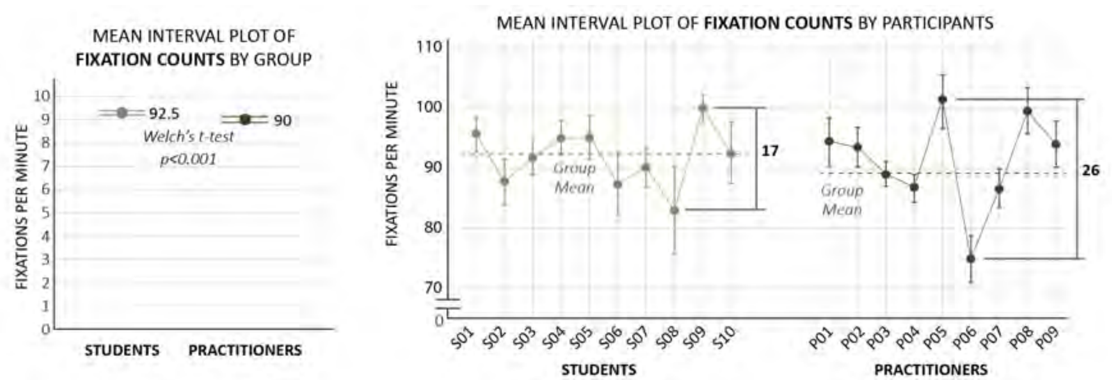



(a) (b)

Figure **6-5**. (a) the mean plots of the MICA of the students and practitioners and (b) the mean plots of the MICA of each participant by group.

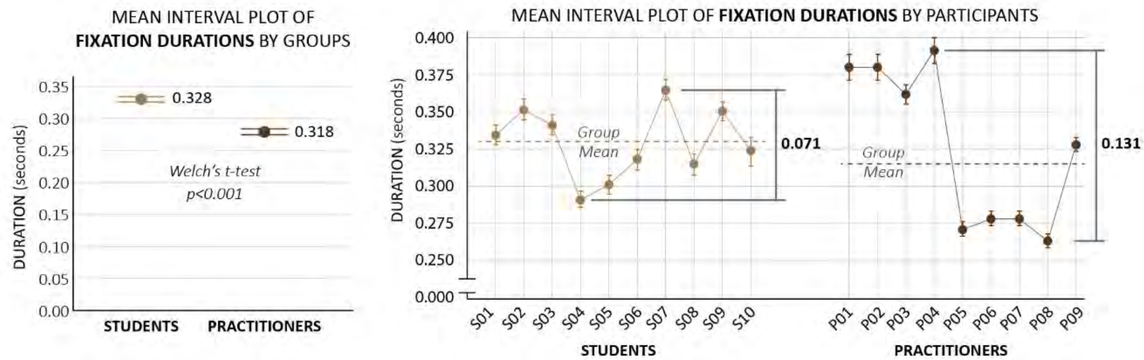
### *6.4.2.2 Fixation Counts and Durations*

The number of eye-fixations and the duration of the fixations were also considered. A fixation is recorded in EyeWorks when a participants' eyes focus on the screen. A Levene test for equal variance was used to determine that the datasets do not have equal variance. A Welch's t-test was run to determine the statistical difference between the number of fixations every minute for the students and practitioners as well as the duration of the fixations. Reporting the total number of fixations would not reflect the different lengths of design sessions, so average fixation count by each minute allows the sessions to be compared. A minute was used because it is a standard measurement of time. At a $\alpha$=0.05 level of significance, the two groups fixation counts and durations are statistically different ($p<0.000$), however, there was statistical significance within the two groups as well. Figure 6-6a shows the mean and interval plots of fixation counts of the students and practitioners as groups and Figure 6-6b shows the mean interval plots of fixation counts for each participant. The practitioners' mean values had a greater range than the students. The same is true for the fixation durations with the groups having statistically different fixation durations ($p<0.000$) at a $\alpha$=0.05 level of significance. Figure 6-7a shows the mean interval plots of the fixation durations for the students and practitioners and Figure 6-7b shows the mean interval plots of the fixation durations for each participant.




(a) (b)

Figure **6-6**. (a) The mean interval plots for the students' and practitioners' fixation counts and (b) the mean interval plots of the fixation counts for each participant.




(a) (b)

Figure **6-7**. (a) The mean interval plots of the fixation durations of the students and practitioners and (b) the mean interval plots of fixation durations for each participant.

### 6.4.3 Cognitive Load of Optimization Cycles

Since the strategies and mental efforts of the participants when organized by experience do not confirm existing theories on expertise, the eye-tracking data were also organized by optimization cycles as an additional evaluation of the sessions. Figure 6-8 shows the scaled MICA, fixation counts, and fixation durations for all Complete, Coarse, Partial, and Independent cycles. While no optimization cycle group had the lowest or highest eye metric consistently, the participants who used Complete Cycles exhibited the largest range of all three eye-tracking metrics. It may be design feedback in optimization strategies cannot predict design cognitive load.

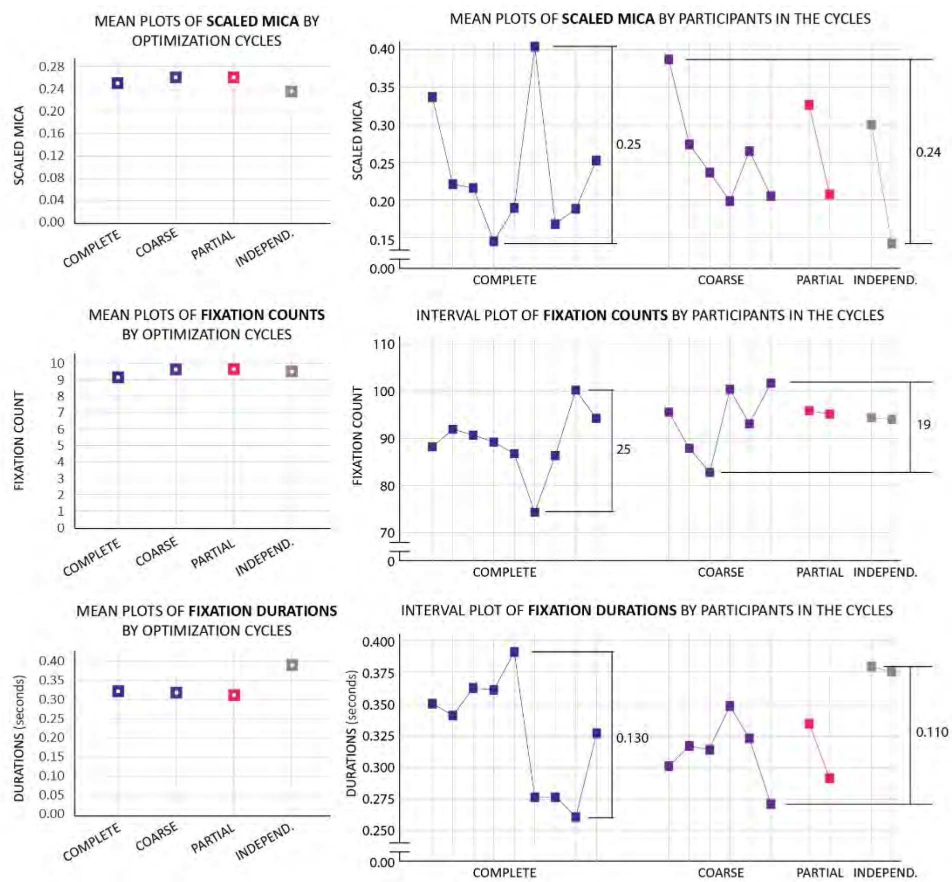



Figure **6-8**. The mean values of the optimization cycles for each of the eye metrics.

## 6.5 Discussion

While the practitioners exerted lower mental effort when averaged over their design sessions, their cognitive loads and design strategies also had a larger spread within their group compared to students. Experienced knowledge is not necessarily an indicator for cognitive effort in this optimization task, which is contrary to what was expected from previous research [1]. When considering their optimization cycles, fewer students incorporated design feedback into their final solutions which suggests they processed less new information. While it is likely that students are more practiced in solving short optimization tasks from their recent design education, the practitioners may approach problems with more fluid strategies because of broader experiences in application. Although the task prompted designers to use optimization techniques, P01 decided the optimization tool was not necessary at this phase of the project and P02 wanted to be more in control of the output of the design, caring more about form in the conceptual phase of design than specific numerical feedback. Alternatively, six of the nine practitioners included design feedback into their decisions, as identified by their type of optimization cycles but their behaviors varied by repetition of exploration, incorporation of writing, and occurrences of key optimization design events. These characteristics reflect differences in design procedures, but do not necessarily align with receiving new information. It is unclear exactly what about their varying design strategies would prompt a larger spread of different cognitive loads.

Research by Zimmerer et al. [46] acknowledges that design tasks influence eye parameters more strongly than cognitive load, which may provide insight into the spread of cognition in our study. For their research, Zimmerer et al., provided design engineers with different design assignments and posited that the diversity of tasks likely contributed to different gaze behavior. Similarly, the participants in our study were free to proceed with any design process they desired, resulting in different strategies. While our atrium design task was well defined for a building facade, the unprompted development and exploration of a model for optimization may have led each participants' cognitive response to behave as if their design tasks were all different.

It is also possible that the eye-tracking metrics used in this study do not precisely capture mental effort in the optimization design task. While there is a trend in the eye measurement data across students and practitioners, individual designers did not express consistently high or low cognitive effort across all metrics. Fixation count and duration indicate focused attention on one area of a screen, which may not align with receiving new information in a design space with a geometric interface. A designer may look at an area before deciding their next action but is not actively receiving new information. In addition, scaled ICA can be an ineffective measurement for cognitive load when responding to more than one task [43]. In this study's design sessions, the participants performed multiple, integrated actions, including geometry development and optimization refinement, with freedom to progress at their own pace. They decided when to perform each action, with some happening simultaneously, like exploration and writing (participants S04, P03, P05, P06, and P07). Complexity in optimization design processes may increase concurrent tasks, and therefore increase cognitive effort, regardless of expertise, which can hinder proficiency in achieving a design task [55]. We also organized the participants by their optimization cycles to provide an additional structure to discuss differences between the designers' strategies.

Grouping the participants by their optimization cycle revealed that participants who used Complete Cycles had the greatest range of results in all three eye-tracking metrics compared to the other cycles. This result further confounds expected behaviors from the designers as Complete Cycles should, in theory, interpret more new information and therefore increase cognitive load. Zimmerer et al.'s claim that diversity of tasks influence eye parameters more strongly than cognitive load may explain why the eye-tracking data does not align in all three metrics for any one of the cycles. To better understand how optimization techniques influence design cognition, future work should examine the events of the optimization cycles with measurements of cognitive load throughout the sessions. Dissecting the sessions for changes in eye data may reveal additional insight about when designers focused more cognitive effort.

In addition, practitioners often engage with optimization tools over long periods of time during a project's development. The design task in this study was a plausible design problem approachable by all participants but was nevertheless a condensed design challenge. Accounting for how practitioners incorporate optimization tools in application of their work may reveal additional information about their design behaviors and processes. However, describing design behavior on a larger timeline requires additional metrics and introduces challenges in comparing groups of designers with mixed expertise. For the purposes of investigating the impact of design feedback on focused design process, this study provides initial comparisons between of students' and practitioners' optimization strategies and cognitive efforts when responding to the same design task.

### 6.5.1 Limitations

While this work is valuable in understanding how practitioners use optimization tools, there are limitations to the scope of the research. The disciplinary background of the practitioners and students is provided in a summary of the participants, but is not included as a variable in the analysis. While this body of work focuses on difference between students and practitioners, future work can compare differences of disciplinary behavior in optimization tools respond to specific research questions.

In addition, there is a difference between the number of students and practitioners who participated, which may create an imbalance of data feedback. However, each participant produced a large amount of data, creating massive datasets from each session. This research is qualitative in the number of participants included, but quantitative in the amount of data generated. In addition, collecting practitioners' data for design studies is highly demanding. For this study, a member of the research team coordinated meeting with each full-time practitioner, visited each firm through several trips, and set up the research tools to conduct the design sessions at the convenience of the practitioners. The data collected from this process allows us to understand initial differences between students and practitioners in optimization environments.

## 6.6 Conclusion

This paper reported the differences between students and practitioners when using optimization tools in response to a building design task. It used event plots and optimization cycles to examine the designers' behaviors and eye-tracking metrics to consider the cognitive effort exhibited by the designers during their design sessions. Practitioners exhibited a wider range of strategies and mental workload compared to the students, which may result from their experience in using optimization techniques in the built world, however, feedback loops in design optimization processes may also disrupt expected cognitive efforts. Although optimization tools can readily identify solutions with improved design performance, they may also impact design exploration and behavior. Tool developers and optimization design educators may consider examples from established theories in information delivery methods to decrease cumbersome cognition during optimization tasks [56]. As an alternative to classifying strategies by expertise, future research will consider optimization cycles to organize proficiency in design techniques and will further investigate the impact of receiving design information on cognitive load and optimization process.

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**References**

[1] M. Kavakli and J. S. Gero, “Strategic knowledge differences between an expert and a novice designer,” in *Human Behavior in Design*, U. Lindemann, Ed., Berlin, Heidelberg: Springer Berlin Heidelberg, 2003, pp. 42–52. doi: 10.1007/978-3-662-07811-2.

[2] S. Ahmed, K. M. Wallace, and L. T. Blessing, “Understanding the differences between how novice and experienced designers approach design tasks,” *Res Eng Des*, vol. 14, no. 1, pp. 1–11, Feb. 2003, doi: 10.1007/s00163-002-0023-z.

[3] B. Lawson and K. Dorst, “Acquiring design expertise,” in *Computational and Cognitive Models of Creative Design VI: Reprints of International Conference of Computational and Cognitive Models of Creative Design*, J. Gero and M. Lou Maher, Eds., Heron Island, Australia: Key Centre of Design Computing and Cognition, Dec. 2005.

[4] J. Sweller, “Cognitive load during problem solving: Effects on learning,” *Cogn Sci*, vol. 12, no. 2, pp. 257–285, Jun. 1988, doi: 10.1016/0364-0213(88)90023-7.

[5] F. G. W. C. Paas and J. J. G. Van Merriënboer, “The efficiency of instructional conditions: An approach to combine mental effort and performance measures,” *Human Factors: The Journal of the Human Factors and Ergonomics Society*, vol. 35, no. 4, pp. 737–743, Dec. 1993, doi: 10.1177/001872089303500412.

[6] A. Baddeley, *Working Memory*. Clarendon Press/Oxford University Press, 1986.

[7] G. H. Bower, “Cognitive psychology: an introduction,” in *Handbook of learning and cognitive processes: Introduction to concepts and issues*, W. K. Estes, Ed., Hillsdale, New Jersey: Erlbaum, 1975, pp. 25–80.

[8] M. Chi, R. Glaser, and E. Rees, “Expertise in problem solving,” in *Advances in the psychology of human intelligence*, R. Sternberg, Ed., Hillsdale, New Jersey: Erlbaum, 1982, pp. 7–75.

[9] N. Cross, “Expertise in design: an overview,” *Des Stud*, vol. 25, no. 5, pp. 427–441, Sep. 2004, doi: 10.1016/j.destud.2004.06.002.

[10] T. Dissaux and S. Jancart, “Impact of cognitive load associated with learning and using parametric tools in architectural design,” in *XIX Congreso Internacional de Expresión Gráfica Arquitectónica, junio 2022*, Universidad Politécnica de Cartagena, 2022, pp. 643–646. doi: 10.31428/10317/11415.

[11] S. Tan, “Towards an integrative approach to researching design expertise,” *Des Stud*, vol. 74, p. 101017, May 2021, doi: 10.1016/j.destud.2021.101017.

[12] S. Bunt, C. G. P. Berdanier, and N. C. Brown, “Observing Architectural Engineering Graduate Students’ Design Optimization Behaviors Using Eye-Tracking Methods,” *Journal of Civil Engineering Education*, vol. 149, no. 4, Oct. 2023, doi: 10.1061/JCEECD.EIENG-1889.

[13] N. Calpin, and J. Menold, “The cognitive costs of design tasks: the evolution of cognitive load in design and its relationship with design outcomes,” in *ASME 34th International Conference on Design Theory and Methodology (DTM),* St. Louis, Missouri, USA, vol. 6, 2022, pp

[14] N. Calpin, and J. Menold, “The cognitive costs of design tasks: examining cognitive load through verbal and physical indicators,” *J Mech Des,* vol. 145, no. 10, p. 101401, Aug. 2023, doi: 10.1115/1.4062976.

[15] D. Yang, L. Wang, and G. Ji, “Optimization-assisted building design - cases study of design optimization based on real-world projects,” in *the 40th Conference on Education and Research in Computer Aided Architectural Design in Europe (eCAADe 2022)*, B. Pak, G. Wurzer, and R. Stouffs, Eds., Ghent, 2022, pp. 609–618.

[16] L. Wilson, J. Danforth, C. C. Davila, and D. Harvey, “How to Generate a Thousand Master Plans: A Framework for Computational Urban Design,” in *SimAUD 2019*, Atlanta, Georgia: Society for Modeling and Simulation International, Apr. 2019, pp. 113–120.

[17] T. Wortmann, “Model-based Optimization for Architectural Design: Optimizing Daylight and Glare in Grasshopper,” *Technology|Architecture + Design*, vol. 1, no. 2, pp. 176–185, Nov. 2017, doi: 10.1080/24751448.2017.1354615.

[18] E. Touloupaki and T. Theodosiou, “Optimization of building form to minimize energy consumption through parametric modelling,” *Procedia Environ Sci*, vol. 38, pp. 509–514, 2017, doi: 10.1016/j.proenv.2017.03.114.

[19] S.-H. Lin and D. J. Gerber, “Evolutionary energy performance feedback for design: Multidisciplinary design optimization and performance boundaries for design decision support,” *Energy Build*, vol. 84, pp. 426–441, Dec. 2014, doi: 10.1016/j.enbuild.2014.08.034.

[20] J. Felkner, E. Chatzi, and T. Kotnik, “Interactive particle swarm optimization for the architectural design of truss structures,” in *2013 IEEE Symposium on Computational Intelligence for Engineering Solutions (CIES)*, J. Felkner, E. Chatzi, and T. Kotnick, Eds., Singapore: IEEE, Apr. 2013, pp. 15–22. doi: 10.1109/CIES.2013.6611723.

[21] N. C. Brown and C. T. Mueller, “The effect of performance feedback and optimization on the conceptual design process,” in *International Association of Spatial Structures Annual Symposium*, Tokyo, Sep. 2016. [Online]. Available: https://www.researchgate.net/publication/316107726

[22] S. Attia, J. L. M. Hensen, L. Beltrán, and A. De Herde, “Selection criteria for building performance simulation tools: contrasting architects’ and engineers’ needs,” *J Build Perform Simul*, vol. 5, no. 3, pp. 155–169, May 2012, doi: 10.1080/19401493.2010.549573.

[23] J. Nocedal and S. J. Wright, “Chapter 1 Introduction,” in *Numerical Optimization*, Second.2006, pp. 1–9.

[24] P. Heiselberg, H. Brohus, A. Hesselholt, H. Rasmussen, E. Seinre, and S. Thomas, “Application of sensitivity analysis in design of sustainable buildings,” *Renew Energy*, vol. 34, no. 9, pp. 2030–2036, Sep. 2009, doi: 10.1016/j.renene.2009.02.016.

[25] A.-T. Nguyen, S. Reiter, and P. Rigo, “A review on simulation-based optimization methods applied to building performance analysis,” *Appl Energy*, vol. 113, pp. 1043–1058, Jan. 2014, doi: 10.1016/j.apenergy.2013.08.061.

[26] J. Mukkavaara, “Exploration and Optimization of Building Design Solutions using Computational Design,” Doctoral, Luleå University of Technology, 2021.

[27] L. Wang, “Workflow for applying optimization-based design exploration to early-stage architectural design – Case study based on EvoMass,” *International Journal of Architectural Computing*, vol. 20, no. 1, pp. 41–60, Mar. 2022, doi: 10.1177/14780771221082254.

[28] X. Liu, L. Wang, and G. Ji, “Optimization-Based Design Exploration of the Mutual Influence Between Building Massing and Façade Design,” in *2022 Annual Modeling and Simulation Conference (ANNSIM)*, IEEE, Jul. 2022, pp. 487–499. doi: 10.23919/ANNSIM55834.2022.9859405.

[29] W. Peng and J. S. Gero, “Concept Formation in a Design Optimization Tool,” in *Innovations in Design & Decision Support Systems in Architecture and Urban Planning*, J. P. Van Leeuwen and H. J. P. Timmermans, Eds., Dordrecht: Springer Netherlands, 2006, pp. 293–308. doi: 10.1007/978-1-4020-5060-2_19.

[30] T. Wortmann, “Architectural Design Optimization—Results from a User Survey,” *KnE Social Sciences*, Nov. 2019, doi: 10.18502/kss.v3i27.5550.

[31] Z. Tian, X. Zhang, X. Jin, X. Zhou, B. Si, and X. Shi, “Towards adoption of building energy simulation and optimization for passive building design: A survey and a review,” *Energy Build*, vol. 158, pp. 1306–1316, Jan. 2018, doi: 10.1016/j.enbuild.2017.11.022.

[32] S. M. Abdelmohsen and E. Y.-L. Do, “Analyzing the significance of problem solving expertise and computational tool proficiency in design ideation,” in *CAAD Futures*, T. Tidafi and T. Dorta, Eds., 2009, pp. 273–287.

[33] C. J. Atman, R. S. Adams, M. E. Cardella, J. Turns, S. Mosborg, and J. Saleem, "Engineering Design Processes: A Comparison of Students and Expert Practitioners," *Journal of Engineering Education*, vol. 96, no. 4, pp. 359–379, Oct. 2007, doi: 10.1002/j.2168-9830.2007.tb00945.x.

[34] R. Yu and J. Gero, "Exploring Designers' Cognitive Load When Viewing Different Digital Representations of Spaces: A Pilot Study," 2017, pp. 457–467. doi: 10.1007/978-981-10-3518-0_40.

[35] E. Granholm, R. F. Asarnow, A. J. Sarkin, and K. L. Dykes, "Pupillary responses index cognitive resource limitations," *Psychophysiology*, vol. 33, no. 4, pp. 457–461, Jul. 1996, doi: 10.1111/j.1469-8986.1996.tb01071.x.

[36] S. Ahern and J. Beatty, "Pupillary responses during information processing vary with scholastic aptitude test scores," *Science (1979)*, vol. 205, no. 4412, pp. 1289–1292, Sep. 1979, doi: 10.1126/science.472746.

[37] S. P. Marshall, "Method and apparatus for eye tracking and monitoring pupil dilation to evaluate cognitive activity," US6090051A, 2000

[38] EyeTracking, "EyeWorks Software."

[39] S. P. Marshall, "The Index of Cognitive Activity: measuring cognitive workload," in *Proceedings of the IEEE 7th Conference on Human Factors and Power Plants*, IEEE, 2002, pp. 7-5-7–9. doi: 10.1109/HFPP.2002.1042860.

[40] M. Bartels and S. P. Marshall, "Measuring cognitive workload across different eye tracking hardware platforms," in *Proceedings of the Symposium on Eye Tracking Research and Applications*, New York, NY, USA: ACM, Mar. 2012, pp. 161–164. doi: 10.1145/2168556.2168582.

[41] J. N. Czerniak, N. Schierhorst, C. Brandl, A. Mertens, M. Schwalm, and V. Nitsch, "A meta-analytic review of the reliability of the Index of Cognitive Activity concerning task-evoked

cognitive workload and light influences," *Acta Psychol (Amst)*, vol. 220, p. 103402, Oct. 2021, doi: 10.1016/j.actpsy.2021.103402.

[42] A. Korbach, R. Brünken, and B. Park, "Differentiating Different Types of Cognitive Load: a Comparison of Different Measures," *Educ Psychol Rev*, vol. 30, no. 2, pp. 503–529, Jun. 2018, doi: 10.1007/s10648-017-9404-8.

[43] J. Vogels, V. Demberg, and J. Kray, "The Index of Cognitive Activity as a Measure of Cognitive Processing Load in Dual Task Settings," *Front Psychol*, vol. 9, Nov. 2018, doi: 10.3389/fpsyg.2018.02276.

[44] M. A. Just and P. A. Carpenter, "Eye fixations and cognitive processes," *Cogn Psychol*, vol. 8, no. 4, pp. 441–480, 1976.

[45] J.-C. Liu, K.-A. Li, S.-L. Yeh, and S.-Y. Chien, "Assessing Perceptual Load and Cognitive Load by Fixation-Related Information of Eye Movements," *Sensors*, vol. 22, no. 3, p. 1187, Feb. 2022, doi: 10.3390/s22031187.

[46] L. L. Di Stasi, A. Antolí, and J. J. Cañas, "Evaluating mental workload while interacting with computer-generated artificial environments," *Entertain Comput*, vol. 4, no. 1, pp. 63–69, Feb. 2013, doi: 10.1016/j.entcom.2011.03.005.

[47] R. Mallick, D. Slayback, J. Touryan, A. J. Ries, and B. J. Lance, "The use of eye metrics to index cognitive workload in video games," in *2016 IEEE Second Workshop on Eye Tracking and Visualization (ETVIS)*, IEEE, Oct. 2016, pp. 60–64. doi: 10.1109/ETVIS.2016.7851168.

[48] C. Zimmerer, T. Nelius, and S. Matthiesen, "Using eye tracking to measure cognitive load of designers in situ," in *Design Computing and Cognition'22*, Cham: Springer International Publishing, 2023, pp. 481–495. doi: 10.1007/978-3-031-20418-0_29.

[49] S. Bunt, C. Berdanier, and N. Brown, "Optimization strategies of architecture and engineering graduate students: Responding to data during design," in *Computer-Aided Architectural Design.*

*Interconnections: Co-computing Beyond Boundaries. CAAD Futures 2023. Communications in Computer and Information Science*, M. Turrin, C. Andriotis, and A. Rafiee, Eds., Cham: Springer, 2023, pp. 174–189. doi: 10.1007/978-3-031-37189-9_12.

[50] M. T. H. chi, “Two approaches to the study of experts’ characteristics,” in *The Cambridge Handbook of Expertise and Expert Performance*, Cambridge, U.K.: Cambridge University Press, 2006, pp. 21–30.

[51] Wallacei X, “www.wallacei.com.” Makki, M., 2018.

[52] N. C. Brown and C. T. Mueller, “Gradient-based guidance for controlling performance in early design exploration,” in *Proc., IASS Annual Symp.*, Madrid, Spain: International Association for Shell and Spatial Structures, 2018.

[53] C. Preisinger and M. Heimrath, “Karamba—A toolkit for parametric structural design,” *Structural Engineering International*, vol. 24, no. 2, pp. 217–221, May 2014, doi: 10.2749/101686614X13830790993483.

[54] B. Fehringer, “Optimizing the usage of pupillary based indicators for cognitive workload,” *J Eye Mov Res*, vol. 14, no. 2, Jun. 2021, doi: 10.16910/jemr.14.2.4.

[55] J. Sweller, P. Ayres, and S. Kalyuga, “Measuring Cognitive Load,” in *Cognitive Load Theory*, New York, NY: Springer New York, 2011, pp. 71–85. doi: 10.1007/978-1-4419-8126-4_6.

[56] P. Chandler and J. Sweller, “Cognitive load theory and the format of instruction,” *Cogn Instr*, vol. 8, no. 4, pp. 293–332, Dec. 1991, doi: 10.1207/s1532690xci0804_2.

# Chapter 7

# Conclusion

This body of work investigates the progression of designerly behaviors through the development of design space exploration processes and identifies themes and strategies in building optimization. Although the students were able to readily explore a prebuilt design space for improved design solutions in studies 1 and 2, the practitioners exhibited a wider range of strategies when constructing and exploring a model for optimization compared to students in studies 3 and 4. While this work does not intend to make generalizable statements about all designers in these groups, capturing and describing their design behavior is useful in making suggestions for design stakeholders. A recent review of empirical multidisciplinary design studies criticized a lack of generalizability and low industrial relevance of research in related topics [1]. In response, this dissertation also makes suggestions for academia and tool developers to better connect research to application:

## 7.1 Suggestions for Stakeholders

Computational tools are prevalent in design education for 3D modeling and design analysis but evoke different responses from students as they develop into practitioners. Their different behaviors can be leveraged to improve their instruction and may inform tool development.

### 7.1.1 Options for Educators

When accounting for design autonomy, educators may consider which strategies they would like to encourage students to pursue, depending on the learning goals of the course. If an educator would like to illustrate objective relationships across disciplinary goals, a pre-built parametric model may be a useful teaching tool. In the first two studies, the students explored a pre-built design space that provided design performance feedback and their responses suggest informed design decisions. Study 1 reported that 83% of the pre-design students produced improved design solutions from the starting model, despite having never previously used the tool. They grasped the relationship between objectives in model and were able to isolate designs with better quantitative performance while still producing visual diversity. From this study, pre-built models can illustrate design relationships and encourage designers to consider a diversity of objectives. In Study 2, the teams with only two architects or two engineers were able to produce designs with the same efficacy as teams with mixed disciplinary backgrounds. When working in the pre-built model, students accounted for design criteria that were not considered part of their disciplinary scope. Although design limits are pre-determined in a pre-built design space, they may still elicit a variety of solutions and prompt exploratory behavior. In an additional publication, I make a case for parametric models as teaching tools, emphasizing their advantages as providing pedagogical formative feedback [2]. Formative feedback, defined by Shute [3] is "information communicated to the learner that is intended to modify his or her thinking or behavior for the purpose of improving learning." Formative feedback should be timely (immediate feedback about performance), supportive (affirmative of correct answers), nonevaluative (or reduce cognitive load), and specific (reduced uncertainty). Parametric tools can achieve these requirements when illustrating many design topics including urban planning [4], structural design [5], and daylighting [6]. However, educators may want to prompt students to develop their own boundaries for a design, which would require more modeling freedom. Constructing a model from scratch would allow the autonomy in design but may also be time intensive [7] and result in incomplete optimization cycles from students. Nevertheless, researchers suggest the positive inclusion of more optimization strategies in architectural design education [8], [9]. Even if students do not pursue DSE as a strategy in their career, introducing DSE as a way of design thinking may allow them to consider multi-disciplinary design with more precision in future pursuits. Notably, the practitioners from study 4 reported that they have used optimization tools for façade design, sculpture installations, and cost engineering. The knowledge acquired in pursuing optimization thinking extends beyond building design, however, and a student must first learn how to use the tools. Figure 7-1 summarizes the advantages and disadvantages for instruction that are suggested by the design exploration actions of the studies.

**DESIGN ACTION SUMMARY**

| **Design Action** | Exploring a pre-built space | Developing a model for exploration |
|---|---|---|
| **Example** | Study 1 Study 2 | Study 3 Study 4 |
| **Advantages** | ○ Can provide performance feedback | |
| | ○ Illustrates *design relationships*<br>○ Encourages *multi-objective thinking*<br>○ Readily approachable by different disciplines for *collaboration* | ○ Allows for *freedom* of ideas<br>○ Can develop *independent* design goals<br>○ Fully *adjustable* bounds of design space |
| **Disadvantages** | ○ Design limits are predetermined<br>○ Limited scope | ○ Time intensive<br>○ Possibilities may be overwhelming |

Figure **7-1**. Summary of advantages and disadvantages of different design tool approaches for educators.

### 7.1.2 Feedback for Tool Developers

Students can benefit from learning optimization tools, but the programs should also be approachable and useful in supporting their education. Although optimization tools are more widely applied in building design, there are criticisms about its functionality. Wortmann [7] acknowledges barriers to the use of multi-objective optimization, such as long analysis run times and poor user interface. Similarly, Tian, et al. [10] reports that long calculation time, a lack of adequate advertisement, and a lack of standard procedures in optimization are hinderances to the use of optimization tools. In addition, researchers have expressed a need in building design industry to prepare designers to use optimization tools [8], [9], [11]. Both instructional techniques and educational tools may better support students' understanding of optimization processes. In an effort to overcome tool based issues, I provide suggestions to tool developers based on observations from the four studies reported in this dissertation and from existing literature.

Figure 7-2 outlines differences in the studies' tools, illustrating the program structure of the model interfaces, the presentation style of performance feedback, and opportunities for an instructional optimization tool. While Grasshopper was used in all the studies, it was not directly accessed by designers in Studies 1 & 2. Grasshopper script was projected in Shapediver [12], a file hosting tool that allows users to explore a Grasshopper space without editing the original file. Shapediver uses an intuitive interface and reduces the need for designers to learn Grasshopper to explore a design space. Alternatively, Studies 3 &4 required designers to work in grasshopper and prompted them to use optimization tools to find improved solutions. These behaviors require substantial knowledge of the programs and comprehension of disciplinary ideas. The gaps in skillsets between Studies 1 & 2 and studies 3 & 4 are considerable. For interpreting design performance feedback, delivery methods also varied between the studies provided in "presentation style of feedback." Quantitative objective feedback can be provided as a number that the designer must interpret, as in Study 3 and 4, but feedback can also be illustrated. Study 1 used bar graphs and colors to show changes in design performance, and Study 2 projected the two quantitative objects on a section cut of the design. In Study 03 and 04, the objective values were provided as numbers from Grasshopper that could be supplied to an optimization tool. Notably, the optimization program Octopus actively plots design options in an objective space that designers can explore. However, only three of the nineteen participants in Study 4 used Octopus. Tool designers may consider how to better highlight advantages of their programs so that designers recognize their visual benefits. Nevertheless, it may be difficult for a tool developer to predict how a designer will use their tool. As observed in the first two studies, students can readily use parametric tools and explore pre-built design spaces, but from studies three and four, constructing a design space for higher-level analysis was shown to elicit a range of unexpected design strategies. Previous researchers have recognized the challenges of navigating optimization tool feedback and Peng & Gero proposed an additional computational tool that supports decision-making by acting as a liaison between the designer and optimization tools [13]. While the tool was useful in their study, the tool did not attempt to educate the designer. Furthermore, there is a gap between pre-built parametric tools and full freedom design space exploration tools that could be addressed by an instructive optimization tool, identified in Figure 7-2.

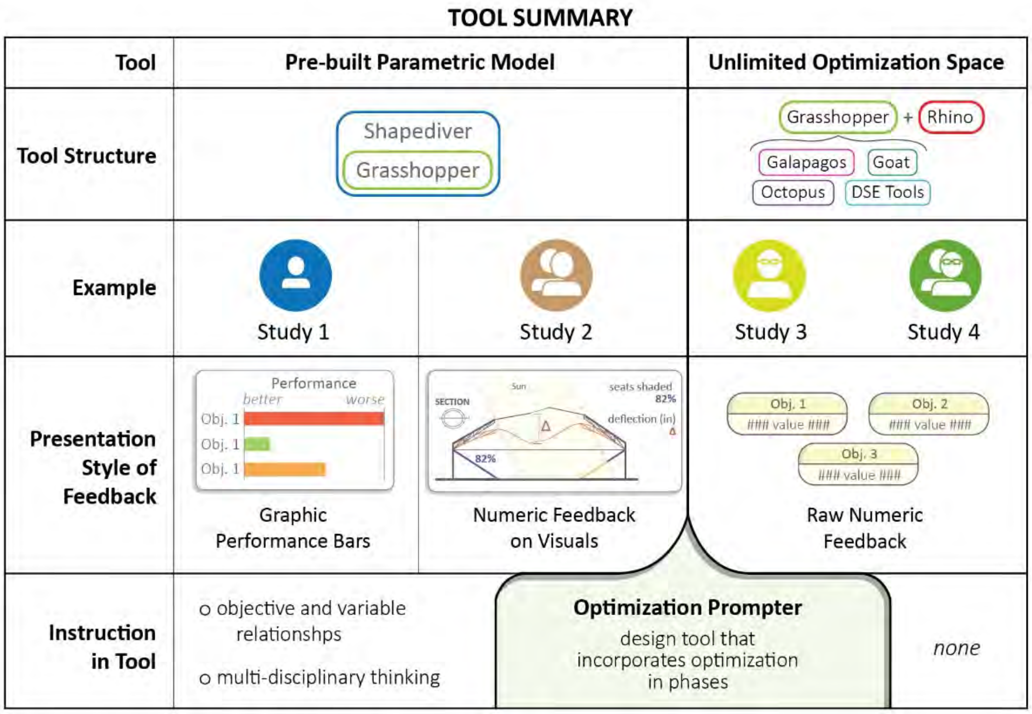



Figure **7-2**. Summary of tools illustrating the tool structure, presentation style of feedback, and instruction opportunities in the tools.

As a potential solution to introduce optimization techniques to developing designers, I propose the concept of an optimization tool called The Optimization Prompter. This tool would guide designers from manually searching for improved solutions to incorporating optimization feedback into their decisions. Through a series of phases, the design space would unlock more editable variables, or parameters, for the designer to explore and introduce new objectives to consider. At a later phase, the user would be introduced to an optimization element that would search the design space and display design options on a 2D or 3D plot. Next, the designer could control which parameters and objectives they want to include in their optimization search. Additional optimization strategies can be introduced, such as weighing the importance of objectives for optimization. A summary of these phases is provided in Figure 7-3. Pre-built models would be required for this tool, but could vary by building type, project site, and disciplinary application. An instructional tool like the Optimization Prompter may lead designers to perform more Complete Cycles, incorporating performance feedback into their design.

**The Optimization Prompter**

INCREASED FREEDOM

| Phase | I | II | III | IV | V | VI |
|---|---|---|---|---|---|---|
| Parameters | 3 | 10 | 10* | 10 | 10<* | 10<* |
| Objectives | 1 | 3 | 3* | 3 | 3* | 3<* |
| Optimizer | - | - | - | Yes | Yes* | Yes*† |

*Can change which parameters and objectives are explored
†Can weight objectives

Figure **7-3**. Summary of the phases suggested in The Optimization Prompter tool.

Applying the information collected from this dissertation, I have made suggestions for educators and tool developers with interests in optimization. Instructors can leverage student behavior when exploring a design space to teach design concepts and tool developers can create an instructional tool for design optimization. These suggestions are not exhaustive for all stakeholders but provide initial ideas for encouraging design space exploration strategies.

## 7.2 Limitations and Future Work

Although this dissertation reports findings from four research studies, spanning across different levels of experience and methods of assessment, there are still gaps in the work. Each study has different sets of participants and different design tasks, which introduce numerous variables between the results. However, holding the variables constant would reduce the accuracy of the studies in other ways, such as reducing the appropriateness of design tasks to the research questions. As established by McGrath, when conducting studies on people, precision in one dimension of the research will inevitably reduce accuracy in another [14]. Nevertheless, there are limitations to the extent of this body of work that needs to be addressed.

While this dissertation makes suggestions for academia, none of the research studies involve student performance in response to classroom instruction, which limits application of the results to direct changes of pedagogies. Monitoring student behavior throughout a course or after receiving instruction with parametric and optimization tools would address research questions pertaining to student learning. This paper does not discuss learning styles or pedagogical techniques, which would add context to the development of designers. In particular, describing differences in disciplinary education may impact how a designer uses DSE tools. Chapter 2 acknowledges some disciplinary differences of design education and Chapter 4 focuses on disciplinary composition in teams, but this dissertation does not distinguish differences between architects and engineers for the studies discussed in Chapter 3, 5, and 6. Future work can investigate disciplinary differences to address the gap in knowledge regarding how pedagogy may impact design behavior in optimization tools.

The tools used in these studies were also highly specific, which narrows the application of the results to all types of parametric or optimization environments. Optimization techniques can be used in other building design tools, such as Dynamo for Revit or coding in Python, which may produce different types of data. However, the tools used, Rhino and Grasshopper, are prominent in the building design industry and provide an initial understanding of behavior in DSE tools. This paper does not discuss details of Rhino, Grasshopper, or Shapediver, or report their potential drawbacks and limitations from a design perspective. The validity of the digital tools has been well established through their common use by researchers, educators, designers, and tool developers, so it is assumed that these tools adequately support design decision making.

In addition, several characteristics of the studies are subjective, which can pose difficulties for repeatability and applicability to broader populations. Qualitative goals, such as “appearance” in chapter 3 or “iconic” in chapter 4, are not clearly defined and were open to interpretation by the participants who may not have interpreted the words with consistent definitions. When evaluating the quality of the designers, as in chapter 4, differences of interpretations may have impacted the statistically insignificant results. However, in architectural building design, qualitative goals are inherently subjective and letting participants respond with their own interpretations was authentic to their design thinking and behavior.

Future work will continue to consider designer development across levels of education and investigate opportunities to improve designer performance within DSE tools. Research from studies 3 and 4 will further examine cognitive effort associated with optimization behavior to suggest new understandings for models of design processes in complex, DSE environments. In addition, future work will consider the role of pedagogy in preparing students to use parametric and optimization tools effectively and how tool instruction can better support design strategies.

## 7.3 A Final Thought

The studies presented in this dissertation scale across the development of DSE designers’ strategies and use increasingly sophisticated methods to assess design behavior. Existing research protocols were used, including event recordings, eye-tracking metrics, and professional evaluations, and established design processes frameworks were employed to develop a novel measurement for classifying optimization behavior. By identifying strategies, outcomes, and cognitive efforts of evolving designers, this dissertation highlights advantages and challenges of using multi-objective tools and emphasizes difference in design techniques by level of experience. Design, in any medium, is a complex task and there are opportunities to investigate each stage of the work further through additional research questions. Nevertheless, this work contributes to understanding design space exploration strategies in academia and practice and provides insights about designerly behaviors when solving multi-disciplinary challenges in emerging building design tools.

### References


[1] M. Nguyen and C. Mougenot, "A systematic review of empirical studies on multidisciplinary design collaboration: Findings, methods, and challenges," *Des Stud*, vol. 81, p. 101120, Jul. 2022, doi: 10.1016/j.destud.2022.101120.

[2] S. Bunt, "Parametric Tools as Teaching Instruments in Architectural Education," in *2023 NCBDS: Known and UnKnown Territories*, Fargo, North Dakota: National Conference on the Beginning Design Students, 2023.

[3] V. J. Shute, "Focus on Formative Feedback," *Rev Educ Res*, vol. 78, no. 1, pp. 153–189, Mar. 2008, doi: 10.3102/0034654307313795.

[4] M. Schnabel, "Architectural parametric designing," in *Communicating Space(s): 24th eCAADe Conference Proceedings*, Volos, Greece, 2006, pp. 216–221.

[5] N. C. Brown and C. T. Mueller, "The effect of performance feedback and optimization on the conceptual design process," in *International Association of Spatial Structures Annual Symposium*, Tokyo, Sep. 2016. [Online]. Available: https://www.researchgate.net/publication/316107726

[6] Q. Liu, X. Han, Y. Yan, and J. Ren, "A parametric design method for the lighting environment of a library building based on building performance evaluation," *Energies (Basel)*, vol. 16, no. 2, p. 832, Jan. 2023, doi: 10.3390/en16020832.

[7] T. Wortmann, "Architectural Design Optimization—Results from a User Survey," *KnE Social Sciences*, Nov. 2019, doi: 10.18502/kss.v3i27.5550.

[8] W. Peng, "Teaching reform and optimization design of architectural performance course," *Int J Soc Sci Edu Res*, vol. 4, no. 9, pp. 48–52, 2021.

[9] J. M. Cichocka, W. N. Browne, and E. Rodriguez, “Optimization in the architectural practice,” in *22nd International Conference of the Association for Computer-Aided Architectural Design Research in Asia (CAADRIA)*, P. Janssen, P. Loh, A. Raonic, and M. A. Schnabel, Eds., Hong Kong: The Association for Computer-Aided Architectural Design Research in Asia, 2017, pp. 387–397.

[10] Z. Tian, X. Zhang, X. Jin, X. Zhou, B. Si, and X. Shi, “Towards adoption of building energy simulation and optimization for passive building design: A survey and a review,” *Energy Build*, vol. 158, pp. 1306–1316, Jan. 2018, doi: 10.1016/j.enbuild.2017.11.022.

[11] J. S. Gero and S. Sarkar, “How to make design optimization more useful to designers,” in *ANZAScA*, 2005.

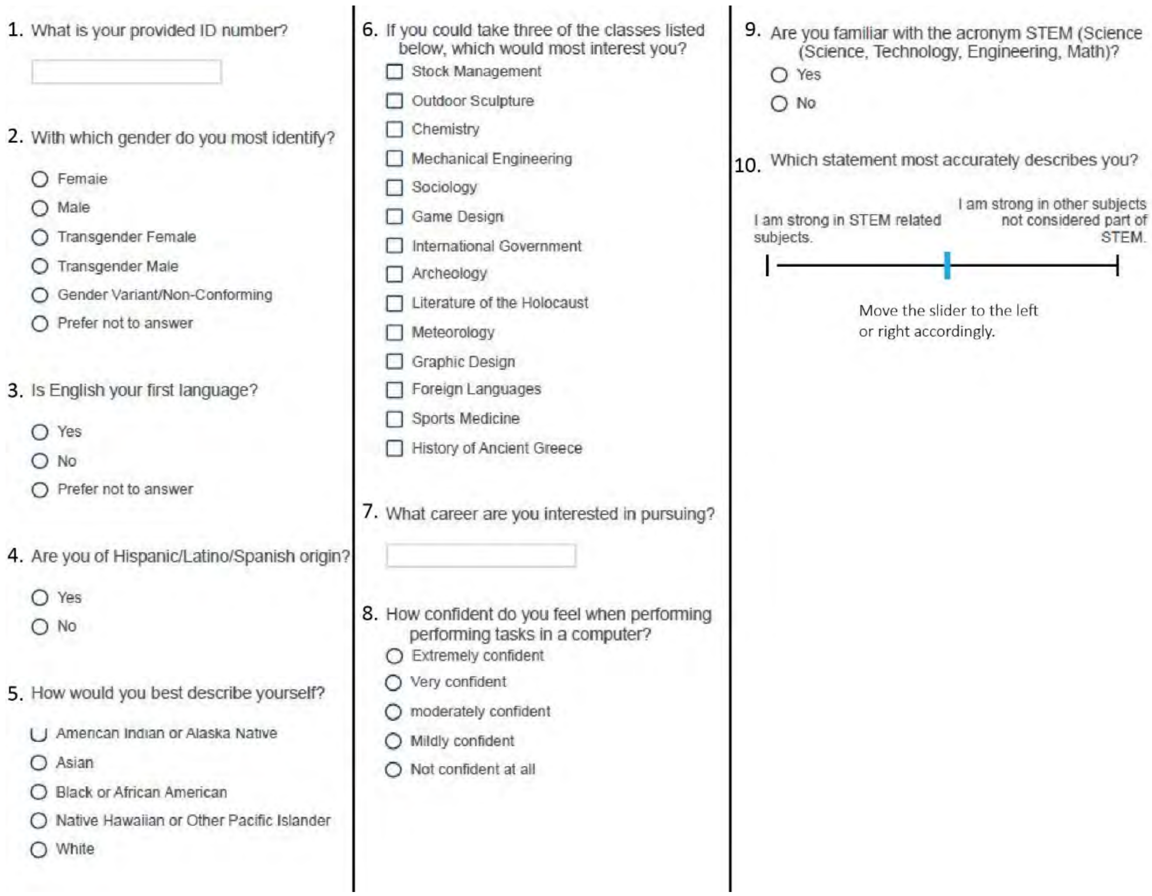
[12] Shapediver GmbH, “Shapediver.” Wien, Austria, 2019.

[13] W. Peng and J. S. Gero, “Concept Formation in a Design Optimization Tool,” in *Innovations in Design & Decision Support Systems in Architecture and Urban Planning*, J. P. Van Leeuwen and H. J. P. Timmermans, Eds., Dordrecht: Springer Netherlands, 2006, pp. 293–308. doi: 10.1007/978-1-4020-5060-2_19.

[14] J. E. McGrath, “Method for Study of Groups,” in Groups: interactions and performance, New Jersey: Prentice-Hall Inc., 1984, pp. 31–37.

# Appendix A

The Pre-design task survey (Figure A1) and post-design task survey (Figure A2) for Chapter 3 (study 1) are presented below. The pre-design task survey was provided to the study's participants at the beginning of the design study, prior to explaining the design task details. The post-design task survey was provided to the participants after completing the design task:


1. What is your provided ID number?

2. With which gender do you most identify?
   - Female
   - Male
   - Transgender Female
   - Transgender Male
   - Gender Variant/Non-Conforming
   - Prefer not to answer

3. Is English your first language?
   - Yes
   - No
   - Prefer not to answer

4. Are you of Hispanic/Latino/Spanish origin?
   - Yes
   - No

5. How would you best describe yourself?
   - American Indian or Alaska Native
   - Asian
   - Black or African American
   - Native Hawaiian or Other Pacific Islander
   - White

6. If you could take three of the classes listed below, which would most interest you?
   - Stock Management
   - Outdoor Sculpture
   - Chemistry
   - Mechanical Engineering
   - Sociology
   - Game Design
   - International Government
   - Archeology
   - Literature of the Holocaust
   - Meteorology
   - Graphic Design
   - Foreign Languages
   - Sports Medicine
   - History of Ancient Greece

7. What career are you interested in pursuing?

8. How confident do you feel when performing performing tasks in a computer?
   - Extremely confident
   - Very confident
   - moderately confident
   - Mildly confident
   - Not confident at all

9. Are you familiar with the acronym STEM (Science (Science, Technology, Engineering, Math)?
   - Yes
   - No

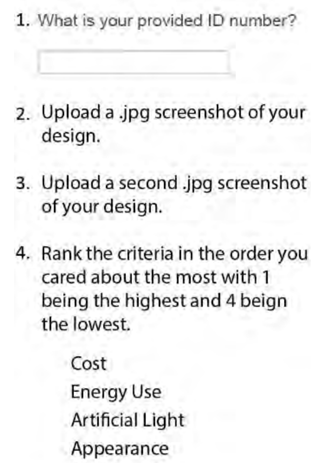
10. Which statement most accurately describes you?

I am strong in STEM related subjects.

I am strong in other subjects not considered part of STEM.

Move the slider to the left or right accordingly.

Figure **A1**. The pre-design task survey for Chapter 3.



1. What is your provided ID number?

2. Upload a .jpg screenshot of your design.

3. Upload a second .jpg screenshot of your design.

4. Rank the criteria in the order you cared about the most with 1 being the highest and 4 beign the lowest.

   Cost
   Energy Use
   Artificial Light
   Appearance

Figure **A2**. The post-design task survey for Chapter 3.

# Appendix B

The performance objectives for the parametric model from Chapter 3 (study 1) were calculated by multiplying the normalized values of the variables by a coefficient, based on the variables' approximate proportional impact on the objective, and adding the results. Table B1 provides the coefficients for each variable for each performance objective. A dash indicates that the variable has no impact on the performance objective:

Table **B1**. The coefficients for calculating the performance objectives from Chapter 3.

| Variable | Cost | Energy | Darkness |
|---|---|---|---|
| Shape | 0.1 | 0.05 | 0.1 |
| Height | 0.37 | 0.18 | 0.24 |
| Top rotate | 0.12 | 0.05 | 0.05 |
| Middle height | 0.05 | | 0.05 |
| Middle scale | 0.08 | 0.05 | 0.08 |
| Top scale | 0.08 | 0.05 | 0.08 |
| Window pattern | - | 0.22 | 0.4 |
| Color | - | - | - |
| Window Thickness | 0.04 | 0.18 | - |
| Wall Thickness | 0.08 | 0.22 | - |
| Base | 0.08 | - | - |
| TOTAL | 1 | 1 | 1 |

## Appendix C

Figure C1 shows the site plan and the design task that was provided to the participants from Chapter 4 (study 2). The design task was provided in paragraph form with design criteria embedded so the designers would need to identify the design goals on their own observation. Two of the criteria aligned with architectural values: that the design be iconic and site appropriate. The other two requirements aligned with engineering goals: that the roof shade 82% of seats during noon on the summer solstice and not exceed a maximum deflection limit of l/180. The shading goal was determined by inspecting existing stadiums for how many seats were shaded on average during the summer solstice. This threshold was also shown during model exploration and test sessions to approximate a percentage goal that was achievable under many variables' settings to allow for design flexibility but would challenge the participants to respond to the need for shade. A deflection of l/180 is a typical limit for several types of structures in building codes.

(a)

*You and your design partner are tasked with designing a stadium roof for the 2032 Olympics. The roof should be iconic, but also appropriate to the surrounding site context. Although a city has not been selected for the 2032 Olympics, it will be located in a tropical climate and you are provided with general site context. At least 82% of the seats should be shaded when the sun is at the position shown in the Shapediver model. Additionally, the roof must not exceed deflections of l/180 and the longest span is 740'. The structure is made out of steel.*

(b)

Figure **C1**. (a) The site plan (b) and design task for Chapter 4.

## Appendix D

Used in Chapter 4 (study 2), Figure D1 shows the names of the variables and graphic representations of what they change. All variables, except "truss depth," could impact the overall visual appearance of the model. Meanwhile, the criteria to be appropriate on site was most affected by "plan shape," "hole scale," and "angle of roof." For the quantitative criteria, "truss depth," "hole scale," "bay count," and "roof height" directly impacted deflection, and the "cover size," "hole angle," "hole scale," and "roof height" greatly impacted the percentage of seats shaded. The variables slid on different increments, depending on the decimal places of the units. Participants were provided with the Figure D1 graphic with the design task to help navigate the model's variables.

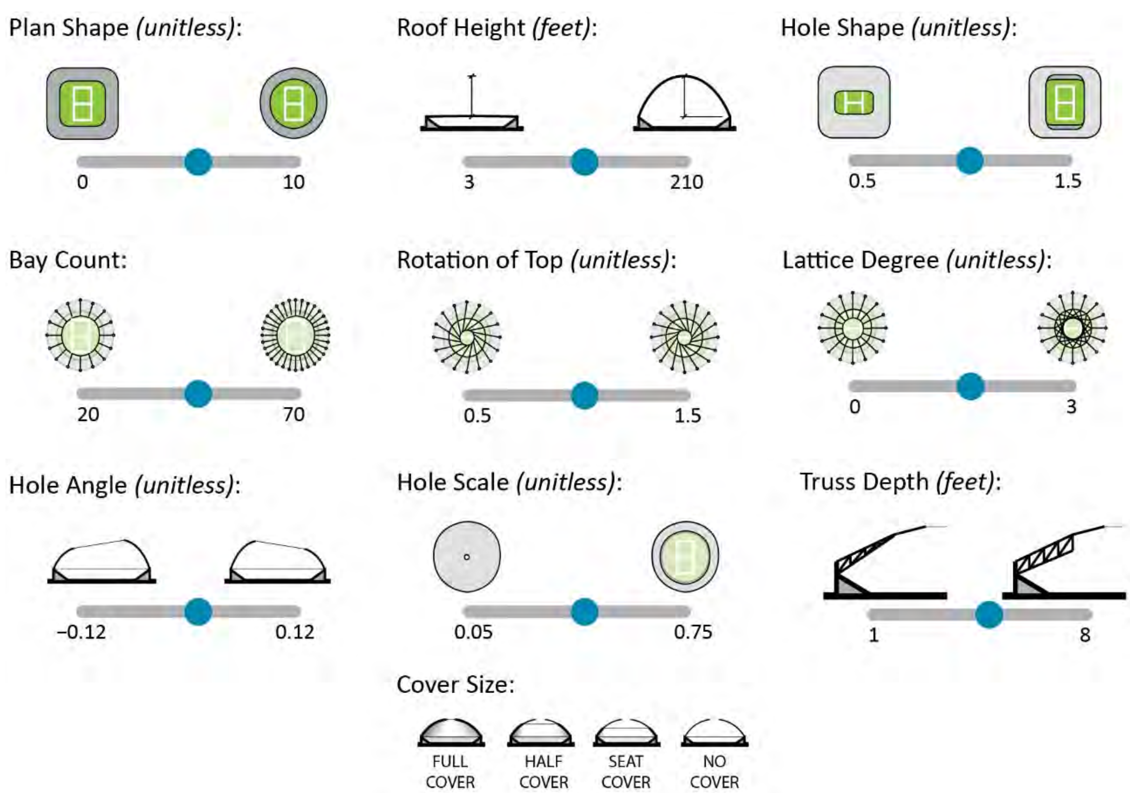



Figure **D1**. The ten editable variables in the design tool with their name, images of what they change in the model, and the range of their values for Chapter 4.

The stadium roof model from Chapter 4 (study 2) was developed in Grasshopper and used Karamba3D [69] to perform live deflection calculations of the roof as participants changed the variables. The participants did not directly interact with Karamba3D, but the structural analysis program ran in the background while they worked. The percentage of seats shaded was calculated within Grasshopper by projecting the angle of the sun on August 15 (an approximate date for the Olympics) for a theoretical tropical climate approximately 12 degrees north of the equator on seats visible in the section cut. Figure D2 shows the tool's section cut display and two quantitative feedback metrics.

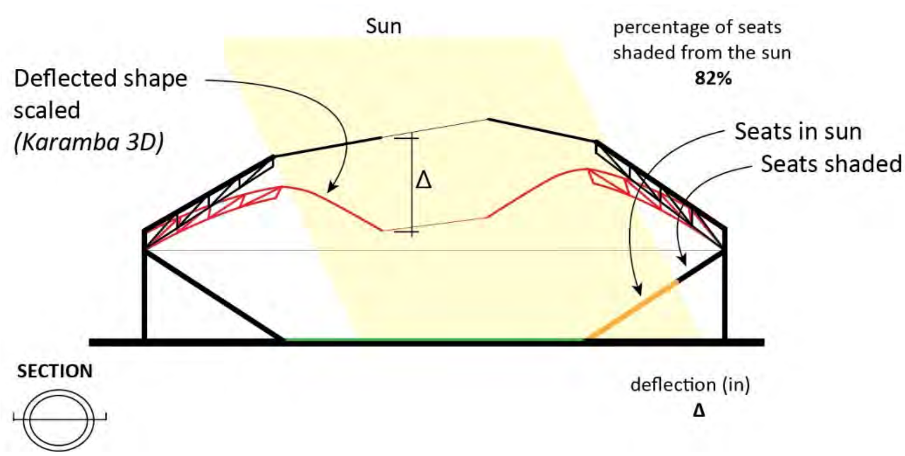
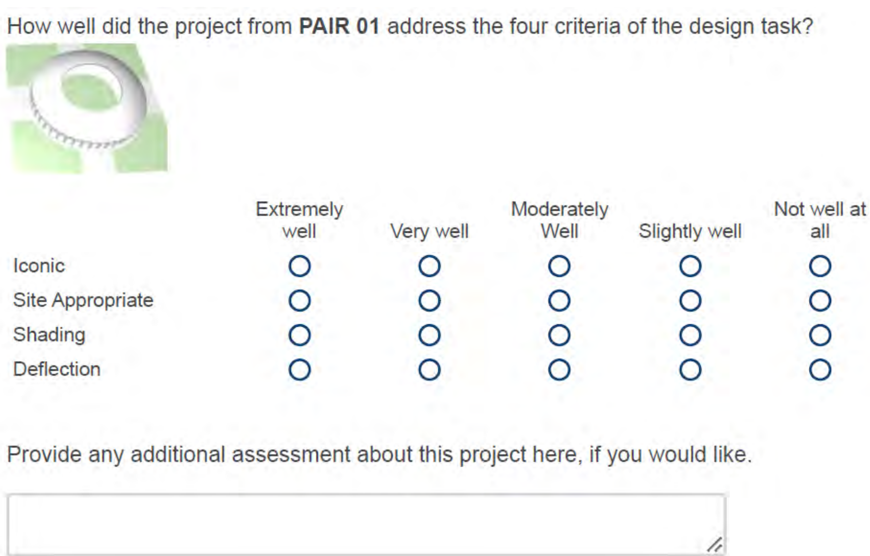



Figure **D2**. The tool's section cut display, showing the maximum deflection, deflection shape, and the percentage of seats shaded from the sun for Chapter 4.

# Appendix E

The four professionals from Chapter 4 (study 2) were asked to review twelve projects: 6 were the same for all professionals and 6 were different. The professionals responded to the research request independently and remotely through the online survey tool, Qualtrics. They were provided with a link to view, but not download or edit, the teams' deliverables document that included the teams' summary statement and screenshots of their design. The projects were renamed "Pair XX" so that the professionals did not know the disciplinary association of the participants or the team's identity. Figure C1 shows an example of one of the project's evaluations from the online survey. A small image of the specific project was supplied in addition to the pair name to make sure the professionals were evaluation the correct project.


How well did the project from **PAIR 01** address the four criteria of the design task?

| | Extremely well | Very well | Moderately Well | Slightly well | Not well at all |
|---|---|---|---|---|---|
| Iconic | O | O | O | O | O |
| Site Appropriate | O | O | O | O | O |
| Shading | O | O | O | O | O |
| Deflection | O | O | O | O | O |

Provide any additional assessment about this project here, if you would like.

Figure **E1**. Example of a project's evaluation question for the professionals' survey for Chapter 4.

## Appendix F

Below are the post-design session interview questions from Chapter 5 and 6 (study 3 and 4). Additional questions about the designers' behaviors were asked on an individual basis, such as their thought process when performing certain acts like starting a second design file.

1. Can you tell me about your strategy for completing this design challenge?
2. Did you find any aspect of the process difficult? If so, what?
3. What did you find to be the easiest?
4. What were the criteria on which you based your design?
5. Why did you pick the two criteria that you picked?
6. What was your envisioned goal for this project?
7. How do you feel your final designs aligned with these goals?
8. If you had more time, would you do anything differently for your design?
9. If you could have interacted with the client, what might you have asked?

**VITA**

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S. Bunt, C. Berdanier, and N. Brown. "Optimization strategies of architecture and engineering graduate students: Responding to Data During Design," in *Computer-Aided Architectural Design. Interconnections: Co-computing Beyond Boundaries*, M. Turrin, C. Andriotis, A. Rafiee, Eds., Delft, The Netherlands: CAAD Futures 2023, July 5-7 2023, pp. 174-189.

S. Bunt, C. G. P. Berdanier, and N. C. Brown, "Observing architectural engineering graduate students' design optimization behaviors using eye-tracking methods," *Journal of Civil Engineering Education*, vol 149, no. 4, June 2023, doi: 10.1061/JCEECD.EIENG-188.

S. Bunt, L Hinkle, A. Walton, N. C. Brown, "Relationship between High School STEM Self-Competency and Behavior in a Parametric Building Design Activity," in *2023 ASEE Annual Conference & Exposition*, Baltimore, Maryland: American Society of Engineering Education, June 25, 2023.

S. Bunt, and N. C. Brown, "Design efficacy and exploration behavior of student architect-engineer design teams in shared parametric environments," *Buildings*, vol. 13, no. 5, 1296, April 2023, doi: 10.3390/buildings13051296.

S. Bunt, and N. C. Brown, "Evaluating profession-based vocabulary in teams of architecture and engineering designers," in *Structures and Architecture: A Viable Urban Perspective?* M. F. Hvejsel, P. J. S. Cruz, Eds., CRC Press, Aalborg, Denmark, July 2022, pp. 1239-1246,

S. Bunt, and N. C. Brown, "Homogeneity versus heterogeneity in architect-engineer design teams," in *Proceedings of the IASS Annual Symposia, IASS 2020/21*, International Association for Shell and Spatial Structures, 2020. pp. 1-12(12).